Trading strategies

and

their implementation into portfolios

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy

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UNIVERSITY OF LIVERPOOL

October 2014

Table of Contents

List of Tables

Chapter four – Implementing a market neutral strategy

Chapter five – Return on equity (ROE) momentum strategy

List of Figures

Chapter five – Return on equity (ROE) momentum strategy

Acknowledgements

First and foremost I want to thank my supervisor Jason Laws for his continuous support throughout the years and the continuous reliability. Thank you for your trustworthiness, suggestions and advices.

Furthermore, I would also like to express my gratitude to my parents for their continuous encouragement during all these years and the sacrifice made to allow me to study in England. Thank you for giving us the faith and ambition to try as much as we can.

Also, I am delighted to have had the chance to study at the University of Liverpool; the University has provided an encouraging learning environment throughout my studies and the atmosphere was really fruitful.

Abstract

Trading strategies and their implementation into portfolios

By: Rayan Husseini

This thesis examines how to implement financial statement analysis to form some investment ideas. Specifically, we are looking at strategies such as value (going long on stocks with a high F-score and short on stocks with a low F-score), and a momentum strategy going long on stocks that have an increase in return on equity (ROE).

Findings suggest that we are able to generate excess returns even after controlling for risks and recommend that the understanding of financial statement can help investors to form investment decisions and give a competitive edge over other investors in the market. There are a few lessons that investors can learn from the findings of this thesis. Value investors should focus on value firms. Momentum investors should pursue an investment strategy among firms with an improvement in return on equity. They could also benefit from forming a portfolio based on both investment ideas, which should protect them from economic downturn and offer an interesting portfolio.

INTRODUCTION

Value investing has been a constant investment tool in the development of investment strategies; since local and international investors are becoming more sophisticated it is not surprising to see the wake of a growing use of stock picking in financial markets. Following the extension of the seminal work of Benjamin Graham and David Dodd (1934) with the use of financial ratios equities have become a popular way to make return out of a portfolio.

In this context of this wide use of financial statement by market participants, providing the best investment tool could give a competitive edge over other investors and has become even more crucial. In fact, with the reliable investment approach it is possible to derive an interesting portfolio.

Due to the poor global economic environment, stock prices are affected by downward changes, however in practice those investors or market participants who can reliably identify value traps by picking winners rather than potentially bankrupt company will profit from their superior forecasting ability.

The work on Piotroski(2000) is not new but we intend in this thesis to provide a refresher by updating the back testing and offer a new application of the f-score by analysing its impact on some common strategies more specifically we form a market neutral portfolio.

Our analysis contribute to the literature by incorporating the f-score on a market neutral strategy and applying the f-score to any kind of companies after pursing a financial check's as opposed to Piotroski's proposition to incorporate the financial health checks on a universe of low price-to-book stocks, therefore we believe that we contribute to the literature by updating the back testing and apply the F-score to a broader set of investable universe and analysing its impact on a variety of simple strategies.

Also we created a migration table where investor is able to see whether a stock is staying in his portfolio from one year to another. Also among the different strategies we were looking at different investment horizons. Accordingly, the rational of this thesis is to investigate the predictive power of the f-score but also the combination of a momentum strategy looking at the ROE as an investment tool, from both statistical and a performance point of view we examined the use of forming a long and a short portfolio by going long stocks rated within 7 to 9 and shorting stocks rated within 0 to 3. The results of the different portfolio are outperforming the benchmark.

Additionally, we examined which criterion was more relevant than another something that has not been done before and one of our major contributions in the literature.

Using data from 1991 to 2012, we developed the F-score, the strategy was then tested using different period's horizon a 3-month, 6-month and a 12-month investment horizons. Despite the fact that we do not account for transaction costs, most portfolio retain produced positive returns. The long-short strategy appears to be the best portfolio despite during pre-crisis time a high drawdown due to the fact that we are losing on both side of the market. Another conclusion from our results is that during crisis time our portfolio is performing really well due to high performances and in terms of forecasting accuracy.

Overall, we depart from existing work in several respects. First, we developed a new back testing approach applying the strategy on different portfolios; secondly we apply a new momentum strategy using ROE as an investment strategy something that has not been done in the past. A recent development in the literature has been the application of the f-score as a market neutral portfolio.

This thesis is organized as follows chapter one provides the motivation for value investing, chapter two gives some insights on the use of Piotroski's model in the current environment, chapter three describe the statistics, chapter four look at implementing a market neutral strategy and finally chapter five provides investors with a new momentum strategy which involves looking at Return-on-Equity.

Chapter one – The motivation for value investing

1.1 The history of value investing

This chapter explores some of the shared views on the nature of value investing; academicians and practitioners may be surprised by the degree of overlap in the perspectives. The timelessness of their views is striking, and some of their research is very applicable to the current environment. Value investing undoubtedly started with the ideas on investment that Benjamin Graham and David Dodd began teaching at Columbia Business School in 1928 and commenced to apply throughout their 1934 text, Security Analysis, by developing financial ratios from the accounting record of companies as a key element of investment decisions. Since then, value investing has been compared to an investment paradigm where technologies and science interact with ideas.

By definition, value investing relies on selecting stocks that trade for less than their intrinsic values. Graham and Dodd (1934) describe those kinds of purchases as: “Investment commitments where the buyer is making a well-considered and legitimate commitment in an enterprise with an attractive future letting his private enthusiasm run away with his judgment” (p.368, *Security Analysis*). Also, Graham and Dodd (1934) said: “Traditionally the investor has been the man with the patience and the courage of his convictions” (p.15, *Security Analysis*).

If an analyst is convinced that a stock is worth more than its value then he pays for it; this kind of strategy can be done with two possible techniques: buying at a time when the market is low or finding individual stocks which are undervalued and are available even at times when the market is not low. Therefore, the strategy can be described as buying stock at a depressed level and selling stocks when the market is over-optimistic. The margin of safety was at the very heart of Graham’s approach to investing (the significance resides in the difference between prices on the one hand and indicated or appraised value on the other. Equally, the growth stock also known as glamor stock refers to company whose earnings are expected to grow at an above-average rate relative to the market, this approach may provide some form of margin of safety to investors as the future prospects are conservatively made and provided it shows a satisfactory margin in relation to the price paid); the term describes a price well below its intrinsic value, the price a fully informed sophisticated investor would pay for the company.

Substantial work supporting the Efficient Market Hypothesis (EMH) has been done over the years. Efficient Market Hypothesis signifies that security prices fully reflect all available information and will immediately adjust to reflect market expectations. However, a number of anomalies have been found which question the validity of the efficient market hypothesis; some of these anomalies are related to the relationship between earnings and returns while others seems to be purely market based. Hence, we will try to give some insights into those anomalies.

Before discussing the anomalies it conveys to present to give some brief insights into the Capital Asset Pricing model, the CAPM offers powerful predictions about how to measure risk and the relation between expected return and risk. Unfortunately, the CAPM reflect theoretical failings; we begin our discussion on the Markowitz efficient frontier, which argues that investors would optimally hold a mean variance efficient portfolio with the highest expected return for a given level of variance. Following the development of the Markowitz portfolio model, several authors considered the implications of assuming the existence of a risk-free asset, an asset with a zero variance; this achievement is generally attributed to William Sharpe (1964), who re-examined the Markowitz (1959) work by showing that investors have homogeneous expectations and optimally hold mean-variance efficient portfolios. Consequently, in the absence of market friction the portfolio will be a mean variance efficient portfolio. Lintner (1965) derived similar theories; the author tested the problem in order to optimise a portfolio held by risk-adverse investors (under which conditions stocks will be held long or short in an optimal portfolio, even when risk premiums are negative/positive). Thus, the literature also refers to the Sharpe-Lintner-Mossin (SML) capital asset pricing model.

An investor may want to attain a higher expected return in exchange for accepting higher risk; in consequence, Reinganum (1981) appraised that either the simple one period capital asset pricing model is miss-specified or that capital markets are inefficient – such as portfolios based on firms' size or price to earnings experience different average returns than those predicted by the CAPM.

Because all investors want to invest in the risky portfolio, Fama and French (1995) provided an extensive literature review on long-term market inefficiencies and why markets are displaying anomalies. Furthermore, Fama and French (2008) dissected anomalies that are not explained by the capital asset pricing theory.

1.1.1 Price to earnings

Several studies have examined the relationship between price to earnings ratio and stock returns. It has been suggested that low price to earnings stocks which is define as price over earnings per share will outperform high price to earnings stocks. The rational behind outperforming is that P/E is a variant of a contrarian strategy based on buying losers and shorting winners. Investor's will pay more for a high P/E.

To begin with, Basu (1977) demonstrated that low price to earnings stocks tend to outperform high price to earnings stocks using securities in the New York Stock Exchange and the American Stock Exchange. Firms were ranked annually based on the price to earnings and size effect as of 1st January and put into one of five equally weighted portfolios; the results suggested that a portfolio of low price to earnings stocks will lead to higher absolute return and better adjusted risk than a high price to earnings stocks portfolio over the period April 1957 to March 1971. Traditionally, the price to earnings ratio is used as a measure of stock price relative to earnings, providing investors with a valuation metric: a high price to earnings would mean that investors are willing to pay more for company earnings compared to stocks with lower price to earnings.

In the same manner, Jaffe et al. (1989) examined the relation between stock return and the effects of size and price to earnings over the period 1951 to 1986, suggesting that the price to earnings and size effect is significant over the study period. Reinganum (1981) appraised that the price to earnings effect disappears when size is simultaneously considered, implying that the price to earnings and value anomaly proxy for the same set of factors is missing from the specification of the Capital Asset Pricing Model (CAPM).

Ibbotson and Riepe (1997) in their paper stated that investors will be able to achieve a market-adjusted return of 13.3% when screening stock based on price to earnings ratio. In another endeavour, Dreman and Berry (1995) suggested that earnings surprise might be affected in a positive or a negative way when looking at stock price reaction to analyst consensus earnings surprised by comparing their empirical work on high and low P/E.

Results stated that analyst errors in forecasted earnings surprises have an asymmetrical impact on high and low price to earnings stocks. These findings were certainly not in line with the findings of DeBont and Thaler (1985), who do not find significant results suggesting that analyst earnings forecast errors occur substantially more in low price to earnings than in high price to earnings. Accordingly, Doukas et al. (2004) studied the dispersion of analysts' earnings forecasts effects implying that stocks with greater disagreement earn higher returns and found greater disagreement among value stocks than on growth stocks partly due to higher risk in value stocks.

Also, Dreman and Berry (1995) tested whether stocks are fully priced after an earnings surprise[1] and suggested that value stocks are mispriced by investors.

Similarly, as part of their analysis of the role small minus big (SMB)[2] and high minus low (HML)[3] play in the return generating process, Fama and French (1993) examined the behaviour of a broad sample of stocks grouped into quintile portfolios by their price to earnings ratio on a yearly basis over the period from July 1963 to December 1991. Fama and French (1993) found that returns are related to risk characteristics like size, earnings/price, cash flow, book to market equity and because these patterns are not explained by the capital asset pricing model, they are called anomalies.

One potential source of market inefficiency is the inappropriate market responses to information. Inappropriate responses to information implicit in the price to earnings ratios are believed to be caused by exaggerated investors' expectations regarding growth in earnings and dividends. Thus, optimistic information regarding growth in earnings can be reflected in price to earnings ratios, with over-optimistic reaction leading to high price to earnings and over-pessimistic expectations leading on average to low price to earnings. Price to earnings (PE) is in consequence a variant of a contrarian strategy based on buying losers and shorting winners. The industry revealed recently that nearly 80% of analysts choose the forward PE as their preferred valuation method. A consequence of a better or lower expected earnings surprise can in fact be linked to an appropriate response to information.

In summary, performance measures indicated that low price to earnings stocks experience superior abnormal risk-adjusted return relative to the market, whereas high price to earnings have relatively inferior risk-adjusted return relative to the market.

1.1.2 Size effect

There is some significant evidence that size is part of the premise of value investing. Indeed, several authors have examined the impact of size measured by the market value on risk-

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[1] Positive surprises for low price to earnings firms result in significantly above market returns; the impact is however to a lesser extent the same on high price to earnings firms. Similarly, negative impact on high price to earnings firms is perceived by the market as a greater impact than on low price to earnings firms due to the implication of the stocks' expectation among investors.

[2] The return to a portfolio of small stocks less the return to a portfolio of large stocks.

[3] The return to a portfolio of high book to market stocks less the return to a portfolio of low book to market stocks.

adjusted returns. The theory suggests that small firms consistently experience significantly higher returns than big firms.

For instance, Banz (1981) scrutinized a size effect in stock returns implying that stock with low market capitalization should outperform stock with high capitalization. In fact, Banz (1981) have presented strong evidence that small firms earn abnormally high risk-adjusted returns by comparison to large firms. Chan et al. (1991) examined the cross-section return on Japanese stocks and one of the four variables was the size effect appraising that small stocks achieve higher returns than large stocks. Similarly, Chan and Chen's (1991) main concern was why small capitalization stocks earn higher returns than large size companies and suggest that this is due to the characterization of the risk. In other words, firms might be exposed differently to risk factors in the sense that their stock prices react more sensitively to changes in the economy and they are less likely to survive in high economic conditions. As an example, firms that are less efficient and have higher costs of production are less likely to react to changes in technology.

Zarowin (1990) stated that the tendency for losers to outperform winners is due to the size effect[4] since losers tend to be smaller than winners. Recently, Zhang (2006) argued that stocks that are small and have a low analyst following exhibit higher evidence of mispricing.

In summary, firm size is a major efficient market anomaly. Size effect must be considered in any event study as this factor has been proven to account for the risk measurements.

1.1.3 Book to market effect

There is some evidence that the book to market ratio[5] can help investors to earn abnormal returns.

Rosenberg et al. (1985) found a significant positive relationship between book to market and returns and has evidenced that such strategy is against the efficient market hypothesis. Similarly, Lakonishok et al. (1994) demonstrated that the strategy consisting of buying low book to market has a lower average return than simply buying high book to market.

Chan et al. (1991) came upon the same strong relationship when looking at the Japanese market[6]: firms with high book to market outperform firms with low book to market. In addition,

[4] Fama and French (1992) argued that the cross section of stock returns could be explained by three risk factors: an overall market factor and factors related to firm size and book to market equity.

[5] This ratio relates the book value of equity and the market value of the same equity. Book value per share = Shareholder's equity – Preferred stocks/ Average outstanding common shares.

Chan and Chen (1991) found that firms the market judges to have poor prospects – signalled by a firm with low stock prices and high ratios of book to market – have higher returns than firms with strong prospects. Later on, Chen and Zhang (1998) confirmed that firms with high book to market indeed exhibit significantly low earnings, higher financial leverage, more earnings uncertainty, and are more likely to cut dividends compared to low book to market firms. Identically, Capaul et al. (1993) elucidated and analyzed the return earned by a portfolio[7] whose investor is holding high price to book ratio against a portfolio where the investor is holding low price to book ratio, and once again results are in line with previous findings.

Strong support for this ratio was provided by Fama and French (1992), who examined the relationship between market beta, size, price to earnings, leverage and book to market in the cross section of average stock returns, demonstrating that, used alone, the variables' size, price to earnings, leverage and book to market have explanatory power. In fact, they have proved the relationship between book to market and average return to be strong and positive and highlighted the importance that risk across stocks is multidimensional. Their suggestion was to define the size effect as a proxy for one dimension and market equity (ME) plus the book to market (BE/ME) ratio as another proxy for risk. In a similar attempt, Lewellen (1999) provided further information on the risk and characteristics behind book to market by focusing on building a portfolio of book to market ratio to see whether it predicts time variation in the expected returns and further if those returns can be explained by a risk factor. The results were consistent with the idea that a strong relationship between book to market and returns can be found at a fixed point in time.

Moreover, Berk et al. (1999) looked at the change in firms' risk throughout time by investigating variables such as book to market and size, which appear to be economically interpretable characteristics of the firms. Similarly, Cooper (2006) stated that low book to market firms are less sensitive to economic conditions and have lower systematic risk; thus, investors should be conscious that low book to market firms have lower beta against the market. Despite the fact that there is no consistent risk factor between high and low book to market firms as spotlighted by Daniel and Titman (1997), Rosenberg et al. (1985) argued that investors who are buying long high book to market firms and shorting low book to market firms will achieve an

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[6] Chan et al. (1991) examined the cross-section return on Japanese stocks using four different variables: earnings yield, size, book to market ratio and cash flow yield. Portfolios were formed on the basis of the four variables and significance was found among the four variables when an investor is trying to achieve higher returns in the Japanese market.

[7] Results were compared across six countries over the period January 1981 to June 1992 and suggest the existence of a value growth factor in each country.

average monthly return of 0.36% during a 12-month window, even after taking into account the size effect across the portfolio. In addition, Fama and French (1992) stated that on average returns rise from 0.30% when forming a portfolio of low book to market (BE/ME) to 1.83% for a high book to market portfolio.

In summary, studies that have used publicly available ratios to predict future stock returns and have provided evidence in conflict with the efficient market hypothesis represent an interesting challenge to the notion of rational markets, as factors that should impact on returns – also called systematic risk – are not efficient, whereas a book to market ratio seems to be capable of capturing future returns.

1.1.4 Reversal effect

In addition to studies supportive of the use of ratios to predict overall stock market returns, many other studies were supportive of the view that, over the long term, extreme performances on stock returns tend to reverse. Stocks that have performed best in the recent past seem to underperform the rest of the market, while stocks that appear to have the worst performance in the recent past seem to offer above average returns.

In essence, DeBont and Thaler (1985) advocated that value stocks perceived as underperforming stocks subsequently reverse to outperform the market and prior winners subsequently underperform the market. Lakonishok et al. (1994) said: “Value strategies might produce higher returns because they are contrarian to naïve strategies followed by other investors” (p.1542, *Contrarian Investment, Extrapolation, and Risk).*

Additionally, Rosenberg et al. (1985) inspected a specific return reversal strategy which consists of buying stocks with lagging specific return in the previous month where they expect the return to be reversed in the following months. “The strategy calculates the difference between the investment return for the previous month on the stock and a fitted value for the return based upon common factors in the stock market in the previous month” (p.48, *Persuasive Evidence of Market Inefficiency*).

Likewise, Jegadeesh (1990) and Lehmann (1990) made evident that investors can benefit from shorter-term reversals return; in fact, investors who are able to distinguish stocks that have performed poorly in the previous week or month can benefit from a contrarian strategy and generate subsequent returns. Similarly, Dissanaike (2002) find a reversals effect when dissecting past stock market losers in the FTSE 100, with a tendency for past losers to outperform past winners.

Investors are therefore wondering whether the reversal effect can account for the risk taken. According to Debont and Thaler (1985), value stocks are fundamentally more risky than growth stocks and the compensation for outperforming can be described as compensation for risk taken. Petkova and Zhang (2005) found evidence that value stocks exhibit higher risk in bad times whereas growth stocks are riskier than value stocks in good times. "In bad times, value firms are burdened with more unproductive capital, finding it more difficult to reduce their capital stocks than growth firms do, the dividends and returns of value stocks will hence co-vary more with economic downturns. In good times, growth firms invest more and face higher adjustment costs to take advantage of economic conditions" (p.68, *Is Value Riskier Than Growth?*).

Therefore, the asymmetric beta dispersion between value and growth results from the asymmetry in capital adjustment, allowing investors to benefit from a reversal effect when selecting stocks.

1.1.5 Cash yield effect

Several studies had made evident that a strategy that buys companies with high yield relative to low yield securities will earn subsequent returns.

As suggested by Litzenberger and Ramaswamy (1979), there is a positive but non-linear relationship between expected return and dividend yield. According to Chan et al. (1991), the return difference between two extreme groups that buy high and low cash flow yield leads to higher returns. "Since firms are reluctant to cut dividends, a substantial reduction is a clear signal of a firm with cash problems" (p.1468, *Structural and Return Characteristics of Small and Large Firms*). Also, Miller and Scholes (1982) found that the relationship between common stock returns and dividend yield can be attributable to the knowledge that the firm will declare any dividends.

Miller and Modigliani (1961) described the change in the dividend rate as: "A change in the market price would not be incompatible with irrelevance to the extent that it was merely a reflection of what might be called the informational content of dividends. That is, where a firm has adopted a policy of dividend stabilization with a long established and generally appreciated target pay-out ratio investors have good reasons to interpret a change in the dividend rate as a change in management's views of future profit prospects for the firm" (p.430, *Dividend Policy, Growth, and the Valuation of Shares*). In other words, investors should be indifferent as to whether a firm pays dividends or retains cash, since this should just translate directly into future dividends for the investor.

Those investors who suggest that dividend yield is an important component in stock return have explained the variation in stock prices by comparing the ability of forecasted dividends and forecasted abnormal earnings. Bernard (1995) found that dividends explain 29% of the variations in stock prices whereas 68% is explained by the cross section of book value and earnings forecasts.

Bernartzi et al. (1997) examined the earnings performance of US firms that changed their dividends over the period 1979 to 1991 and reported a strong correlation between lagged and contemporaneous dividend and earnings change. They found that change in dividend cannot really predict future changes in earnings.

In summary, the reasoning from those studies is that when dividend yield is high it implies that investors are expecting or requiring a high return on stocks. This has been proven to be more frequent during a poor economic environment when investors perceive higher risk for investment and require a high rate of return. Thus, it has been suggested that if you invest during this risk-averse period you will experience above average returns.

1.1.6 January effect

Several studies that do not support the efficient market hypothesis have found December trading volume abnormally high for stocks that decline during the previous year and significant abnormal returns during January for those loss stocks. Hence, empirical evidence suggests that markets perform well during the month of January.

Bhardwaj and Brooks (1992) searched the January market effect as a value strategy, suggesting that this effect results in high January returns for depressed stocks by analyzing whether the January anomaly is related to price effect or to firm size effect, and revealed that low share price stocks earn abnormal returns in January before tax transactions cost. Jaffe et al. (1989) considered the period 1951 to 1968 in their study, and revealed the difference between January and other months to be that price to earnings appears to be significant only in January.

Other studies have shown that the small size firm effect occurs entirely in January, more precisely in the first two weeks of January. Please refer to Keim (1983) and Reinganum (1983). Can we really take into account the January effect as those literatures are quite old but we believe that the January anomaly is still significant in our market? Recently Cooper et al. (2006) contributed to the literature by saying that the January effect is a good indicator for the stock market return of the rest of the year and demonstrated strong evidence that the January effect does exist.

It can be concluded that, because of transaction costs, arbitrageurs should not eliminate the January tax-selling anomaly.

1.1.7 IPOs

During the past few years, several studies have observed the long-run returns on initial public offerings (IPOs)[8] and indicated that investors are facing some form of under-pricing when forming an investment. In other words, investors who acquire the stock after the initial adjustment do not experience abnormal returns.

Loughran and Ritter (1995) expressed their concern that firms issuing equity earn lower than average returns in the future three to five years than non-issuing firms with similar characteristics. Also, they viewed whether firms issuing stock via an initial public offering and seasoned equity offering have been a poor investment for investors. The results showed that firms subject to issuing via an IPO or a seasoned equity offering (SEO)[9] underperform firms non-issuing for five years after the offering date. "Since most SEOs occur after a period of high returns, we address whether the poor subsequent performance is merely a manifestation of long-term return reversals" (p.24, *The New Issues Puzzle*).

Loughran and Ritter (1997) explained that the operating performance of issuing firms displays substantial improvement prior to the equity offerings, but then deteriorates. They found that many of the issuing firms have an improvement in profitability before the offering and face a decline of profitability after the offering. However, Ikenberry et al. (1995) demonstrated that the average abnormal return for a four-year buy and hold strategy based on the announcements of open market share repurchases can earn 12.1% for the period 1980-1990. For value stocks the average abnormal return is 45.3% because of undervaluation; the repurchasing is more likely to be significant; and they hypothesized that the markets treat repurchase announcement with scepticism.

Finally, Brav et al. (2000) reported that the outperformance following a seasoned equity offering is more significant among small growth firms and suggest that the outperformance is the result of size and value effects in returns.

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[8] Initial public offering is a type of public offering where shares of stock in a company are sold on a securities exchange for the first time.

[9] Seasoned equity offering is a new equity issue by an already publicly traded company.

Thus, investors can form investment decisions based on IPO and SEO.

1.2 The momentum strategy in the market efficiency

1.2.1 Macroeconomic momentum

This part of the chapter will try to describe all the different momentum strategies applied in the literature. Momentum in stock returns refers to the tendency of stocks that have performed well (poorly) to continue to perform well (poorly).

Levy (1967) claimed that investors who buy stocks at the current price that are subsequently higher than the average stock price realized over the past 27 weeks are able to benefit from abnormal returns. Likewise, Jegadeesh and Titman (1993) considered a strategy that buys stocks based on their returns over the past first, second, third and fourth quarters, suggesting that stocks that generate higher than average returns in one period also generate higher than average returns in the following period. The momentum effect is presumably the strongest evidence against the market efficiency hypothesis.

Jegadeesh and Titman (2001) found a momentum effect and propounded the view that momentum strategies yield to superior returns by providing further proof based on their past findings, such as whether momentum strategies continue to be profitable for investors. They concluded that, while the performance of individual stocks is highly unpredictable, portfolios of best-performing stocks in the recent past period appeared to outperform other stocks which were lagging in the past period, and argued that the momentum effect presumably represents the strongest evidence against the market efficiency hypothesis. Jegadeesh and Titman attribute this effect to the fact that investors under-react to the release of firm-specific information – a cognitive bias.

It is for these reasons that momentum has attracted academicians wishing to understand the principles of this strategy. Perhaps the momentum strategy is a multifactor explanation of asset-pricing anomalies. For illustration, Gertler and Gilchrist (1994) decided to analyze the source of momentum strategy as described by common factors and firm-specific information; they were followed by Chordia and Shivakumar (2002), who have asserted the importance of common factors and firm-specific information as sources of momentum profit.

Fama and French (1996) have asserted that a momentum strategy's profitability cannot be explained by its unconditional factor exposure: "A momentum strategy may spuriously appear to earn abnormal returns if it tends to load heavily on a factor when exposure to that factor requires a high return" (p.49, *Multifactor Explanations of Asset Pricing Anomalies*).

Thus, Griffin et al. (2003) appraised that macroeconomic variables can explain the momentum returns and suggested that macroeconomic risks that are driving momentum returns are country specific; see also Rouwenhorst (1998)[10].

On the other hand, Chordia and Shivakumar (2002) stated that common factors are related to macroeconomic events that are related to the business cycle of a company. In fact, the authors used variables such as dividend yield, default spread, yield on three-month T-bills and term structure spread to assess momentum strategy, revealing that macroeconomic variables are important in determining the cross-sectional variation in expected returns. Similarly, Liu and Zhang (2008) considered the relationship between macroeconomic risk, factor pricing and momentum profits, implying that higher growth rate of industrial production can help to explain the cross section of returns and momentum returns. For instance, they said: "Winners have higher future growth rate of dividend investment and sales than losers and that the duration of the expected growth spread matches roughly that of momentum" (p.3, *Momentum Profits, Factor Pricing, and Macroeconomic Risk*). Likewise, they found important cross-sectional variation in higher growth rate of industrial production among different industry portfolios; for example, cyclical industries such as consumer durables and energy have large and positive higher growth rate of industrial production whereas health care and utility have negative higher growth rate of industrial production.

In summary, macroeconomic shocks might account for the momentum anomaly.

1.2.2 Overreaction

Several tests have considered whether investors overreact to information displayed by the market.

Barberis et al. (1998) presented a study into investor sentiment regarding how investors form their belief and proposed that investors can earn positive returns by taking advantage of under-reaction and overreaction without carrying more risk. The model appears to be relevant statistically and consistent with experimental evidence. On the other hand, Zarowin (1990) studied stock market overreaction by investigating the overreaction phenomenon among

[10] Rouwenhorst (1998) has explored the sources of return variation in emerging markets, "If the return factors in a group of relatively isolated markets are the same as those found in developed markets, it becomes more likely that the factors are fundamentally related to the way in which investors set prices in financial markets around the world"(p.1440, *International Momentum Strategies*).

investors and by reinvestigating the tendency discovered by DeBondt and Taler (1987) for losers over a past three-year period to outperform winners over the same period. Similarly, LaPorta et al. (1997) claimed evidence of overreaction in growth stocks and value stocks when assessing accounting variables and found that an investor can earn subsequent returns by betting against an overreaction. Moreover, Dissanaike (1997) considered the stock market overreaction hypothesis as to whether or not investors overreact to information due to over-optimism or pessimism. Additionally, Chan (1988) inspected a contrarian investment strategy consisting of buying past losers and shorting past winners. The strategy is formulated on the basis that investors overreact to information and in consequence winners tend to be overvalued and losers undervalued. Also, Conrad and Kaul (1993) argued that the overreaction effect might be explained by factors such as bid-ask biases, infrequent trading and time-varying risk. Also, Fama and French (1996) advised that their three risk factor model can account for the overreaction evidence among investors but not for under-reaction.

Chan (2003)[11] focused on the impact of news on stock market momentum and reversion. He found that stocks with news exhibit momentum while stocks without news do not. Thus, if investors overreact to news, past stock market losers should become winners and inversely winners become losers.

Recently, Tetlock (2007) expressed and developed a new approach to quantify qualitative information by showing that the pessimism expressed in a daily news column from, for example, The Wall Street Journal can have significant downward pressures on prices of the stock indices and found also that an increase in the use of negative words relative to prior stories predicts larger negative shocks to future earnings.

Also, the author demonstrated by a regression analysis and a buy and hold strategy that investors can benefit from examining the difference in optimism and pessimism information expressed by managers on the management committee report. This should in fact yield to subsequent return in the short term and even after earnings announcement.

Also, Tetlock (2007) has examined whether the information relative to management discussion[12] is incremental regarding the firm’s characteristics such as size and analyst followers.

[11] Stock market reactions to news and no news.

[12] This strategy requires investors to assess whether the nonfinancial information is favourable or unfavourable in examining returns. This study looked at the frequency of positive versus negative words in the SEC disclosures. Findings show that results are significant in a short-term window and can be exploited by investors willing to earn subsequent returns.

The change in information appears to be weaker for value firms than for firms with positive earnings surprises; therefore investors willing to benefit from this market mispricing can earn subsequent returns.

Thus, the overreaction to information is a challenge to the efficient market hypothesis. Individuals react differently to the flow of news as they have different beliefs when it comes to make a decision. In other words, heavier weights will be assigned depending on the individuals.

1.2.3 Industry momentum

Academic researchers have exposed an intermediate momentum effect in US stock returns and attributed it to an industry effect, suggesting that strong (weak) industry performance is followed by strong (weak) industry performance over a period of months. Here we are clearly suggesting that investor can benefit from an industry effect.

Fama and French (1996) highlighted that a stock-specific returns momentum strategy should be more profitable than a total return momentum strategy and that the profitability of the momentum strategy cannot be fully explained by the cross-sectional variability or as a reward for being part of an industry risk. Grinblatt and Moskowitz (1999) have considered the momentum effect in the industry components of stock returns – the industry components account for much of the momentum anomaly – and their results found strong evidence of the industry momentum effect even after controlling for microstructure effects and individual stock momentum and even after taking into account the cross-section dispersion. Similarly, Lewellen (2002) tested momentum strategies in terms of return regarding the role of the industry sector, the size and the book to market factors, suggesting that the three factors exhibit strong momentum.

Therefore, the industry momentum effect should be considered when analyzing firms; in fact, by combining the momentum and industry effect investors can better identify stocks to buy to take advantage of the expected trends.

Also, different studies in the literature suggest that value and momentum strategies might be dependent on each other.

Asness et al. (1997) suggested that value and momentum strategies might be dependent on each other by examining value strategies among stocks that have exhibited strong momentum. Value strategies appear to be negatively correlated with momentum strategies and both are positively correlated with return, advising that value should work better if momentum is held constant and vice versa.

Bird and Whitaker (2003) have interrogated the success of a combination between value and momentum strategies and found such kind of strategy capable of outperforming the market. For instance, they examined the performance of value and momentum strategy in the European markets over the period from January 1990 to June 2002 and revealed astonishing abnormal returns.

In summary, investors can try to add an effect to their momentum strategy when they are under the decision-making process.

1.2.4 Buy back

Empirical studies have expressed the motivation to understand evidence supporting the share buyback.

Vermaelen (1981) studied 131 buyback offers and attributed that positive share market reaction to the information was a signal whereby the managers of the firms try to convince shareholders that the shares of the company are undervalued.

Stein (1996) claimed that, when a company's stock is mispriced, a manager can issue overvalued stock or buy back undervalued equity. When stock prices are above fundamentals, rational managers of equity-dependent firms think it more attractive to issue equity, whereas, when stock prices are below fundamental values, managers of equity-dependent firms do not invest, because, for them, investment requires the issuance of stock at a price below their expectations. MacDonald (1993) has disputed that the stock prices reflect the future stream of dividends and asked whether a long-run relationship exists between stock prices and fundamentals. It is well known in the industry that firms facing large capital expenditure to finance new and existing opportunities may pay no dividend for several years; also, it is claimed that managers might manipulate the stock price of their company before issuing buyback shares.

Ikenberry et al. (1995) found that stock prices rise on the announcements of share repurchases and then continue to drift in the same direction in the following years.

Recently, Wang and Johnson (2009) stated that, when a management team is issuing a share buyback announcement, investors should deal with the idea that the company is displaying promising earnings. However, this practice is perceived by the market as a support for the stock price.

1.3 The accruals anomaly

A number of empirical studies have compared the benefits of accrual income with those of cash flows. By definition, accruals represent liabilities and non-cash-based assets; this account includes accounts payable, accounts receivable, goodwill, future tax liability and future interest expense.

Sloan (1996) is certainly among the pioneers giving an extensive explanation of the accruals anomaly, even if, previously, Dechow (1994) compared income directly with cash flow, showing that accrual income more closely measures firm performance as reflected in stock return. Moreover, Dechow et al. (1998) showed that accrual income is a better predictor of future cash flows than current cash flows.

Also, Sloan (1996) suggested that firms with high accruals earn lower returns on average than firms with low accruals and claimed that earning driven by positive accruals earnings (i.e., profits are greater than cash flow from operations) is a bad signal of future profitability and returns. As stated: "Firms with relatively high (low) levels of accruals experience negative (positive) future abnormal stock returns that are concentrated around future earnings announcement" (p.290, *Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?*).

One objective of this part of the chapter is to understand the role of accruals in producing earnings. As Dechow (1994) stated: "The primary role of accruals is to overcome problems with measuring firm performance when firms are in continuous operation" (p.4, *Accounting Earnings and Cash Flows as Measures of Firm Performance: The Role of Accounting Accruals*).

Hence, Fairfield et al. (2003) examined whether accruals are a component of growth in net operating assets and a component of profitability by suggesting that one year ahead return on assets is negatively associated with accruals and growth in net operating assets: "If the overvaluation of accruals relative to cash flows documented in Sloan (1996) is attributable to the market's misunderstanding of the incremental effect on one year ahead ROA (return on assets) of growth in net operating assets, then we would expect to find a similar overvaluation of growth in long-term net operating assets" (p.355, *Accrued Earnings and Growth: Implications for Future Profitability and Market Mispricing*). Thus, one of the primary results is that investors tend to overvalue the implications of accruals and growth in long-term net operating assets.

Zhang (2007) investigated whether accruals capture fundamental investment in working capital. Covering the period 1964 to 2003, he documented that high-growth firms tend to generate low stock returns in the following years, suggesting that investors overestimate the continuing performance of growth firms. Also, Zhang found that accruals co-vary with growth components such as growth in the number of employees, external financing, and cash sales growth, suggesting that accruals capture fundamental investment information.

We follow our discussion with Yu (2005), who has figured out that excluding cash flow from a model linking return and accruals creates an omitted variable problem. This same omitted problem has been confirmed by Livnat and Santicchia (2006), who have detected similar results whether using annual or quarterly data when examining accruals. Similarly, Gerard et al. (2009) inspected the interaction between operating cash flow, earnings, accruals and their association with subsequent stock returns; they reveal that operating cash flow and accruals are negatively correlated with subsequent returns and suggest that firms with negative cash flow and negative accruals are a key driver of the asymmetric performance of accruals and cash flow strategies.

Mashruwala et al. (2006) advanced that the presence of arbitrage risk limits the ability and desire for institutional industries to fully implement the accruals strategy. “Even if smart arbitrageurs were to understand the implications of accruals for future earnings, they are likely to be constrained by excessive exposure to idiosyncratic volatility and transaction costs to eliminate the mispricing related to accruals” (p.5, *Why is the Accrual Anomaly not Arbitraged Away? The Role of Idiosyncratic Risk and Transaction Costs*).

Therefore, one possible reason why the accruals strategy earns subsequent returns is because investors naively focus on earnings. In fact, investors fail to fully price the differing implications of the accruals and cash flow and overweight the accruals anomalies of current earnings when trying to forecast earnings and, in consequence, when this accrual falls investors are surprised about future earnings announcements and subsequent returns correspond to price adjustment. This has been confirmed by Xie (2001) when he appraised that the market tends to overestimate accruals, even if Khan (2008) suggested that accruals are not mispriced and not misunderstood by market participants.

It has long been known that accruals tend to be reversed, hence Houge and Loughran (2000) pointed out that this suggests a natural earnings quality trade; for this reason, LaFond et al. (2005) explored whether investors price accruals quality. They stated: “Accruals quality tells investors about the mapping of accounting earnings into cash flows” (p.296, *The Market Pricing of*

Accruals Quality), and suggested that investors being able to distinguish good quality accruals from poor quality accruals generally associated with larger costs of debt[13] will earn abnormal returns.

Accordingly, Chan et al. (2006) focused on accruals as a potential indicator related to earnings quality for future stock returns. They explored reasons why accruals might be linked with subsequent returns by providing evidence that a firm facing difficulties in generating sales will experience a build-up in inventories, hence the components that accruals increase early might be a sign that sales growth is slowing.

Similarly, Richardson et al. (2006) aimed at examining whether the accrual component of earnings is attributable to temporary accounting distortions that could arise from accrual estimation error and concluded that accounting distortions could be a significant explanation for the diminution of the accruals components and that those distortions would be the results of some intentional manipulation by managers. As a result, Kothari et al. (2006) investigated whether managers of overvalued firms are more likely to revise accruals components upwards to carry the overvaluation. They stated: “One of the predictions of the theory is that overvalued firms’ managers attempt to boost their firm’s reported performance to meet investor expectations” (p.1, *Agency Theory of Overvalued Equity as an Explanation for the Accrual Anomaly*).

In another way, Pincus et al. (2007) cross-examined whether the accruals anomaly is related to country differences in accounting and institutional structures and found the occurrence to be present in countries with common law and in countries allowing an extensive use of accruals. Indeed, in the 90s, Fama and French (1998) provided evidence that the accruals anomaly is likely to occur in countries sharing the same principle in law. In other words, the accruals anomaly characterized by stock markets overweighting accrual is present in only four countries: Australia, Canada, the UK and the US. Their persistence can be explained by the presence of some barriers to arbitrage, and it is more likely to see the appearance of the anomaly in countries where the capital markets are considered most efficient and one of the possible reasons given might be the focus on earnings by investors in those countries.

Therefore, Gerard et al. (2009) came upon a hypothesis that accruals would perhaps perform better during periods of high sentiment[14] and consequently poorly during periods of low

[13] Firms with the best accrual quality enjoy a 126 basis point lower cost of debt than firms with a poor accrual quality

sentiment, in contrast with a cash flow strategy which performs poorly during periods of high sentiment and well during periods of low sentiment. Similarly, Ali and Gurun (2009) scrutinised the effect of investors' sentiment on accruals anomaly and accruals management by claiming that small stocks mispricing per unit of accruals is greater in high sentiment periods in contrast with low sentiment ones.

Finally, Wei and Xie (2008) advocated a strategy where investors can earn subsequent returns by using the accruals and capital investment after adjusting for the Fama-French three risk factors. We believe this strategy is a re-adaptation of Rangan's (1998) work, which investigated whether accruals and capital investment capture the same components. If managers expect the firm's demand to be high they will build up the production capacity and inventory. "Building up production capacity required an increase in capital investment and building up inventory requires an increase in accruals because inventory is a component of current accruals" (p.1, *Empirical Evidence on Capital Investment, Growth Options, and Security Returns*). Each component is assessed to see if individually it provides new information to affect prices, and the outcome propounded that the accruals component and the capital investment component are distinct from each other. In fact, they recommended a strong capital investment effect on accruals and inversely a strong accruals effect on capital investment. As a trading strategy, when forming their portfolio they found that a trading strategy consisting of buying firms in the lowest total accruals quintiles and the lowest capital investment and simultaneously shorting firms in the highest total accruals quintiles and the highest capital investment can lead investors to a 15.35% characteristic-adjusted return per year and 12% per year risk-adjusted return.

Recently, it has been stated among the literature that the accruals components seems to be disappearing. For example, Green et al. (2011) studied whether the accruals anomaly is still existent, and suggested that the accruals anomaly has deteriorated in the US stock market to the point that it is not positive anymore. Similarly, Mashruwala et al. (2006) examined whether the accruals anomaly can still earn abnormal returns and found that returns are no longer positive. They suggested that one of the possible reasons behind the accruals anomaly no longer being positive is that the strategy has been overused by hedge fund managers.

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[14] Gerard et al. (2009) found that market sentiment is an important factor in distinguishing stock performance of financially distressed firms for investors and came upon an example by saying that when sentiment is high investors seem to be optimistic about the returns of a financially distressed company whereas when sentiment is low investors are pessimistic about the returns of a financially distressed company.

1.3.1 The q theory

Wu et al. (2010) referred to the q theory to understand the accrual anomaly by arguing that firms adjust their accruals in response to discount rate changes[15]. As stated in their paper: "When the discount rate falls, more investment projects become profitable, increasing accruals, and future returns decrease on average because the lower discount rate means lower expected returns going forward. When the discount rate rises, fewer investment projects become profitable, decreasing accruals, and future returns increase on average because the higher discount rate means higher expected returns going forward" (p.178, *The Q-theory Approach to Understanding the Accrual Anomaly*). In a similar manner, Polk and Sapienza (2009), using the Tobin's q theory, reported a form of mispricing in the market by focusing on discretionary accruals to measure a firm's level of abnormal cash earnings. Firms with high discretionary accruals have a relatively low stock of returns in the future and in consequence are overpriced. Also, the authors reviewed the relationship between investment[16] and future stock return.

Bakke and Whited (2010) studied the effect of the stock market on investment by using the variation in Tobin's q in their model. By using their model, they try to identify characteristics of the firms that use external information in stock prices as well as those that exploit stock market mispricing.

Overall, accruals have become a major component in accounting as they increase the amount of information contained in a company when analyzing financial statements and they are a major strategy used by practitioners.

1.4 The value premium

1.4.1 Debt capacity

Numerous studies have analyzed the impact of announcements of debt capacity changes on stock prices. In efficient markets, this should result in a change in the firm's value and consequently impact the stock prices.

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[15] A higher discount rate implies less profitable investments and lower accruals while a lower discount rate implies more profitable investments and higher accruals.

[16] Polk and Sapienza (2009) said if a firm is misallocating its resources due to market misevaluation, then subsequent investment should predict risk-adjusted returns, and found that firms with high (low) investment have low (high) stock returns on average. Also, this effect appears to be more significant among firms with higher R&D intensity or higher share turnover.

For instance, Bernanke et al. (1996) used the financial accelerator effect and the credit multiplier of Kiyotaki and Moore (1997) to test the hypothesis that high debt capacity firms are more likely to have higher exposure to risk associated with changes in internal and external funds for investment.

Therefore, if this risk can be priced by the market an investor can benefit from this strategy to earn subsequent returns; thus, investors should expect high debt capacity firms to earn higher returns than low debt capacity firms.

Recently, Hahn and Lee (2009) developed and tested a model on the differential effect of debt capacity on stock returns across financially constrained and unconstrained firms and found that debt capacity is only significant in determining stock return among financially constrained firms. The authors stated: "For financially constrained firms whose investments are below the first best level, higher debt capacity implies a higher sensitivity of collateralized investment to changes in the availability of internal funds: A marginal increase in internal funds will support more borrowing and investment for those firms that invest in assets with higher collateral value" (p.892, *Financial Constraints, Debt Capacity and the Cross Section of Stock Returns*).

These findings support the efficient market hypothesis because they indicate that stock prices react to changes in accounting variables, in this case a change in debt capacity.

1.4.2 Corporate events

Several studies have examined the impact of corporate events on stock prices and how the market impacts such kind of events.

The reaction to mergers is that the stock of the firms being acquired increases in line with the premium offered by the acquiring firm, whereas the stock of the acquiring firm decreases because investors think that they overpaid for the stocks. Smith (1986) gives an extensive review of the capital acquisition process. Also, recently, Gulen et al. (2008) examined the firm level asset investment effects, moreover, corporate events associated with asset expansion such as acquisitions, public equity offerings, public debt offerings, and bank loan initiations. The authors suggested that corporate events tend to be followed by periods of low return whereas events associated with assets contraction such as spinoffs, share repurchases, debt repayments, and dividend initiations are associated with abnormal returns.

Also, Livdan et al. (2009) re-examined external financing anomalies such as firms raising capital earn lower returns compared to firms distributing capital and examined the frequency of equity issuance. The results suggest that firms conducting equity offering underperform firms that do not issue.

In summary, most studies found a positive or a negative impact on stock returns because of corporate events.

1.4.3 Financially distressed firms

A couple of studies have examined the importance of a firm's distress risk factor and stock returns, and revealed that bankruptcy is not systematically rewarded by higher returns and in consequence the size and book to market factors are unlikely to be related to bankruptcy risk.

Dichev (1998) tested the importance of the firm's distress risk factor and its relation to size and book to market and provided evidence about the relationship between bankruptcy risk and systematic risk. As mentioned: "Simple correlations reveal that bankruptcy risk is negatively related to firm size and positively related to book to market. Thus, bankruptcy risk could potentially account for the size and book to market effects if bankruptcy risk is a systematic risk priced into returns" (p.1132, *Is the Risk of Bankruptcy a Systematic Risk?*). The study also explored the risk of bankruptcy by using two well-known models in the literature, the Altman Z-score (1968) and the Ohlson O-score (1980), to study whether bankruptcy risk is a systematic risk priced in subsequent security returns.

In addition, Ovtchinnikov and McConnell (2009) decomposed the relationship between stock prices and corporate capital expenditures and found a strong relationship between stock price and investment to be more significant for certain type of firms such as firms subject to debt, financial distress and information asymmetry, and suggested that firms with more leverage, firms with less cash flow, firms with lower dividends and firms with lower interest coverage are more sensitive in their investment decisions to stock prices.

Campbell et al. (2008) documented the determinants of corporate failure and the pricing of financially distressed stocks using US data over the period 1963 to 2003. They presented evidence that failure risk cannot be adequately explained by the measure of distance to default inspired by Merton' (1974). Also, they show that stocks with a high risk of failure tend to deliver low average returns. Similarly, Griffin and Lemmon (2002) examined the relationship between book to market, distress risk and stock returns. Their findings showed that the low average returns of firms with high distress risk are driven by the poor stock price performance of these low book to market firms and suggest that firms with high distress risk exhibit the largest return reversals around earnings announcements and that book to marked effect is largest in small firms with low analyst coverage.

Vassalou and Xing (2004) documented and calculated distance to default and found evidence that distressed stocks with low distance to default have higher returns, but this evidence is restricted for small value stocks.

Playing on financially distressed firms has always been part of the decision-making process of investors as, if you are willing to take more risk, subsequent returns can be earned from this strategy.

1.4.4 Bid-Ask value strategy

The results of several studies have examined the response of stock return with the spread in the Bid-Ask – essentially the difference in price between the highest price that a buyer is willing to pay and the lowest for which the seller is willing to sell.

Studies by Stoll and Whaley (1983) suggest that the effect of the bid-ask spread is an important component to take into account when investors want to exploit the potential to earn abnormal returns by exploiting such anomaly.

Morse and Ushman (1983) showed significant increases in the bid-ask spread and revealed that the higher a stock's spread the higher its return. Following this strategy, Amihud and Mendelson (1986) showed during 1961-1980 that the monthly excess return of a stock with a 1.5% spread is 0.45% greater than that of a stock with a 0.5% spread, but the monthly excess return of a stock with a 5% spread is only 0.09% than that of a stock with a 4% spread, and supported the idea that the spread is an important determinant of stock return. The authors concluded that stock returns are an increasing and concave function of the spread. The higher yields required on higher spread stocks give firms an incentive to increase the liquidity of their securities, thus reducing their cost of capital.

In summary, stocks exhibiting a large change in stock price in response to a new information can help investors to benefit from this overreaction. Overall, studies are suggesting that change in the bid-ask spreads is more recurrent in the short term, especially with regard to negative information, allowing investors to benefit from inefficiency in the market.

1.5 Conclusion

To conclude, over the past few years the market has demonstrated some form of inefficiency, in contradiction to the efficient market hypothesis theory. The theory contends that stock price fully reflects information and implies that no group of investors can have access to private information that will allow them to experience above-average returns. From the numerous studies reported in our first chapter we have tried to give investors some brief insights into the previous research and on the different anomalies exploitable out of the market. Thus, when forming their investment decisions, sophisticated investors can benefit from superior above-average returns based on those anomalies. We introduce in our next chapter a new approach which has proven to be efficient as it appears that markets are inefficient.

Chapter two – The use of Piotroski's model in the current environment

2.1 Introduction

The nature of this thesis lies in applying a simple fundamental analysis strategy developed by Joseph Piotroski, who is an Associate Professor of Accounting at Stanford University's Graduate School of Business. Prior to this position, Piotroski was an Associate Professor of Accounting at the University of Chicago's Graduate School of Business. His research focuses mainly on how market participants use financial statement information when forming a decision. He has published research papers in numerous scholarly journals such as the Accounting Review, Journal of Accounting Research, Journal of Accounting and Economics, and The Journal of Finance and he is part of the Editorial Advisory Boards of The Accounting Review, The Journal of Accounting Research, and The Journal of Accounting and Economics.

When screening stocks in high book to market i.e. in order to select an individual stock as an investment, investors need a good source of prospective investments, Piotroski (2000) argued that stocks are suffering more often than not from financial distress. His answer to this was that the incorporation of a simple set of financial health checks including relevant variables that focus on three areas of a firm's financial condition can help an investor to shift the "distribution of the returns". The three areas are: ***profitability***, which provides information about the firm's ability to generate funds internally, the financial ***leverage/liquidity*** of the firm designed to measure changes in capital structure and the firm's ability to meet future debt service obligations and, finally, through performance signals such as ***operating efficiency***.

The model consists of a set of binary financial tests based on profitability, leverage, liquidity and operating efficiency, as mentioned above, where the higher the score, the better the investment is said to be. A stock that passes all the tests would be an excellent investment whilst a stock with a score of zero or one should be avoided. With the exception, as reported in the literature, that you decide to short those stocks.

Piotroski's so-called F-score was not based on some optimized form of backtesting, rather it was a reflection of what prior academic research and practitioners had identified as helping to boost future returns. This chapter is looking at applying the strategy developed by Piotroski (2000) to a universe of stocks such as the S&P 1500[17] and analyzing further if this strategy helps in

[17] The S&P 1500 combines three leading indices, the S&P 500, the S&P MidCap 400 and the S&P SmallCap 600, to cover approximately 90% of the US market capitalization. It is designed for investors seeking to replicate the performance of the US equity market.

distinguishing winners from losers in that particular universe. Also, we intend to rebuild the backtesting and deal with data snooping.

The origin of the idea was developed during the researcher's second year as a PhD student, which was spent working for an investment bank as an intern. With the growing importance in the role of equities to both the international and local investors, the selection of an attractive stock and the ability to ensure the performance return could be a reliable investing tool in the selection process of a portfolio and will give a competitive edge over other investors in the market.

The study was run using advanced programming languages such as SAS[18] to extract data from Compustat[19] and CRSP. Compustat is a database that contains US fundamental statement and market information on active and inactive publicly held companies. It provides insight into a vast range of income statements, balance sheets, statements of cash flows and other data items. The database allows us to compare current and prior years' results on a comparable basis. Annual history is available for most companies back to 1950 and quarterly history back to 1962, with monthly market history back to 1962. In contrast, the CRSP database contains information on the returns, events, beta, and volume data for the NYSE, AMEX and NASDAQ stock markets.

Using relevant data variables, the F-score was estimated using fiscal year data for the period ranging from 30/06/1991 to 31/05/2013. Companies can close their fiscal period in any month of a calendar year. A fiscal year is an accounting period of twelve months and a company's fiscal year corresponds to the calendar year in which it has the most overlap in months. As an example, if a company's fiscal year-end is March 2001, the data in its annual report represents the company's operations for nine months in 2000 and three months in 2001. Therefore, the data would be classified as fiscal 2000 data. In contrast, a calendar year is a period of one year beginning with January 1 and ending with December 31. In this research, fiscal years ending between January and May are assigned to the previous calendar year whereas fiscal years ending between June and December are assigned to the current calendar year. Using the variables DataDate[20] and fyear[21] under Compustat we were able to determine a firm's fiscal year-end.

[18] SAS, also called Statistical Analysis Software System, is an integrated applications system that gives researchers strategic control over their data processing and make possible an unlimited variety of applications. SAS is also a powerful programming language that enables researchers to access, manage, analyze and present their data.
[19] Compustat offers restated data that allows for comparability between current and prior years' results on a comparable basis.
[20] This item indicates the time period to which each item applies.
[21] Data Year – Fiscal.

Here, we wanted to give some brief insight of value investing which was initiated by Graham and Dodd (1934), where they argued that out of favour stocks are often under-priced in the market and therefore "Intelligent investors" may make a profit by identifying those companies. Over the years, a number of leading investors such as Warren Buffet[22], Mario Gabelli[23], and Seth Klarman[24] among others have followed the rules influenced by the school of investment. Graham and Dodd (1934) argued that, while markets were efficient overall, pockets of inefficiency existed. They believed that opportunities for mispricing were most likely to happen in the smaller stocks.

Graham and Dodd (1934) showed that it was possible to find companies that were under-priced in the market, often because investors were too focused on short-term news. They also developed the concept of "margin of safety" where investors should try to always buy shares well below their intrinsic value.

Value strategy is therefore not new and one should not avoid investing in growth stocks, as they tend to offer decent dividend yields which remain attractive in a low interest rates environment. Growth stocks should be able to do relatively well against a low growth backdrop/downturn; also, even in economic storms those stocks tend to have higher margins, earn higher returns for shareholders and have stronger positions. However, such companies are usually a lot more expensive in valuation terms but in a low growth environment they could continue to lead the way.

These days, investors are facing a stock picking paradise, where the apparition of stock picking among practitioners is becoming interestingly consistent in their investment process. The stock-picking approach looks at the quality of a company's business model, what is driving cash flow, sustainability of growth and margin expansion under management decisions. Investors diversify portfolios by growth driver, investment theme, investing in both value and growth stocks and look at market capitalization.

The aim is to diversify their basket to the point that, no matter the market direction, a portfolio will produce positive returns over the long term. It is therefore not surprising that

[22] He is an American investor widely considered one of the most successful investors of the 20th century; he is also the CEO of Berkshire Hathaway and consistently ranks among the world's wealthiest people.
[23] He is an American investor, founder, chairman and CEO of Gabelli Asset Management, a $30 billion global investment firm. Gabelli is said to be a leading proponent of the Graham-Dodd school of security and a pioneer in the application of Graham and Dodd's principles.
[24] He is an American billionaire, founder of the Baupost Group, a private investment partnership, and the author of a book entitled: "Margin of Safety: Risk-Averse Value Investing Strategies for the Thoughtful Investor".

distinguishing winners from losers has attracted much attention from financial agents in the market. Over the past few years, researchers and practitioners have claimed the idea that being able to find a company that is trading at a discount to intrinsic value will generate higher returns (i.e., the actual value of a company may or may not be the same as its current market value).

Nevertheless, investors make buy and sell decisions on the basis of the current price of the securities compared with the perceived values of those securities. Over the long term, investors tend to believe that stocks will reflect the underlying businesses. Also, investors should be cautious when performing their investment ideas as to whether or not the stock price fluctuations will reflect the underlying businesses.

According to circumstances, the investment process is therefore to discover and purchase stocks which are undervalued and hold these until they cease to be a "good value"; successful identification of mispriced stocks is generally possible by personal study of relevant information or by seeking out expert advice in the form of investment as an advisory service. The same approach has been formulated in this research using financial statement variables providing information that might help the ordinary security holder to formulate buy and sell decisions. The idea is to provide a better service when it comes to forming a portfolio.

In the US, higher quality stocks based on the Piotroski measure are relatively inexpensive versus the normal premium they attract. Market turbulence and rising doubts as to the sustainability and therefore duration of the current economic downswing has increased investor interest in lower risk, higher quality equities where buying low versus high beta stocks has proved to be an interesting investment style. In fact, extreme levels of volatility, typically driven by macro-orientated events, create a market that becomes highly susceptible to sudden changes in investor sentiment and market reversals.

In consequence, the motivation of this chapter was to predict a company that can create a stronger value when forming a portfolio. If effective, as mentioned by Piotroski (2000), "The differentiation of eventual winners from losers should shift the distribution of the returns earned by a value investor" (p. 2, *Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers*). After reproducing the F-score, results are consistent with previous findings and by using this strategy an investor can achieve superior performance in distinguishing US stocks.

Overall, Piotroski's model achieves superior performance when used to distinguish winners from losers in a universe. This indicates that the F-score is a promising investment strategy tool in evaluating companies. In summary, here we intend to apply the Piotroski F-score approach by applying the strategy on a bigger universe and by not limiting our screening process on only high book-to-market firms. Also we intend to update the backtesting as part of our contribution to the literature.

Finally, this chapter is organised as follows. Section 2 presents the existing empirical evidence of value investing in the US and overseas and financial statement analysis, and defines the nine financial signals used by Piotroski to differentiate firms. Section 3 presents the data used and discusses the procedures and methods adopted. The results are reported in section 4, which gives an insight into a buy and hold strategy, the data migration stability of the Piotroski model and, finally, analyzes the results of each F-score in terms of returns to see if they are sustainable over time – after plotting some graphs we are looking to find a steady line.

2.2 Literature review

The literature review intends to lay a foundation for the current research. We set the chapter within a research context consisting of relevant research studies directly related to the use of the Piotroski model using working papers as well as articles from different academic journals of research relevant to the subject, and try to link to related ideas over the past few years.

Following a chronological approach, even if this is not all-inclusive, we firstly tend to group by relevance of the topic when it comes to describing the nature of that subject.

Fischer Black[25] (1971) stated: "The random walk theory of stock price behaviour is that the past history of stock price movements, and the history of stocks trading volume, does not contain any information that will allow the investor to do consistently better than a buy and hold strategy in managing a portfolio" (p. 30, *Implications of the Random Walk Hypothesis for Portfolio Management*).

David N. Dreman[26] (1977) emphasized the random walk theory by mentioning: "The efficient market hypothesis is for the birds and what random walk fails to take into account are the psychological influences that play a major and often harmful in professional investment

[25] An American economist best known for his applications of the Black-Scholes equation.
[26] Dreman is an investor and chairman of Dreman Value management. He has published many journal articles and has written four books.

decisions. Random walk is based on the hypothesis that we are basically human computers with consistent rationality. But there is tremendous evidence that we do not behave that way at all" (p. 15, *Psychology of the Stock Market: Investment Strategy beyond Random Walk*).

2.2.1 The premise of value investing

2.2.1.1 High book to market literature review

The above quotations appear to have been reflected in the study of Dreman (1977), where he decided to ignore the random walk theory in his model and to invest solely in companies with a solid financial statement and the lowest price to earnings PEs. When the PE moves up relative to the market average industry/sector, the company should be sold and the money should be reinvested in the most neglected stocks. According to Dreman, buying with the lowest PE could lead to better annual returns than buying stocks that have a PE in the top 10% of the market.

Furthering the discussion, Rosenberg et al. (1985) reported the statistical significance of two strategies: firstly they showed that a strategy that buys high book-to-market and sells stock with low price to book to market firms can generate on average higher expected returns, and the second strategy consists of a simple "specific return reversal" strategy. The success of these two strategies in detecting market inefficiencies as stated by the authors suggests that there are still potential profits to be made out of the market.

Discussion was reawakened by Fama and French (1992) in a study where they argued that the cross section of stock returns could be explained by three risk factors related to the return of stocks. For instance, an overall market factor and factors related to firm size/market capitalization and book to market equity. Fama and French demonstrated that used alone size, PE, leverage and book to market equity have explanatory power.

The study has been realized on all NYSE stocks in June of each year from 1963 to 1991; data were extracted from the CRSP database. Stocks were than ranked and the median NYSE size was used to split NYSE, Amex and NASDAQ stocks into two groups, "small" and "big". Then stocks were split into three book to market equity groups, bottom (30%), middle (40%) and top (30%), where they define book to common equity as the Compustat book value of stockholder's equity, plus balance sheet deferred tax and investment tax credit minus the book value of preferred stocks. The results confirm the same hypothesis, that high book to market strategies outperform the market.

Lakonishok et al. (1994) presented in their study a contrarian strategy on the US market from 1968 to 1994. The contrarian strategies based on ratios such as price to book ratios or past turnover growth were not fundamentally more risky and they demonstrated that, because the stock market is not efficient, financial ratios have predictive power because they are able to capture systematic errors from investors' expectations about future returns. Haugen (1995) argued that the value premium arises because the market undervalues distressed stocks and overvalues growth stocks. In the same manner, Chan et al. (1991) contributed to the finance literature by providing some evidence on the cross-sectional returns in the Japanese market: that earnings, size, book to market ratios and cash flow can help to reveal the relationship between fundamental variables and returns and, accordingly, found strong evidence for the superior performance of value investment strategy.

Clearly, as demonstrated previously by Haugen (1995), if an investor identified those stocks that have performed poorly in the market due to overreaction to poor news, this same investor should buy those stocks and hold them long enough for the market to react and therefore readjust its decisions. This theory follows the evidence suggested by Debont and Thaler (1985) that the stock market consistently overreacts to unexpected bad news and in consequence someone being able to form a portfolio of eventual "losers" will outperform a portfolio of eventual "winners".

Thus, one possibility is the market has a behavioural bias towards growth, for which it tends to overpay. This bias can be explained partly by the hypothesis that the market extrapolates past trends into the future and thus expects the low past growth of value stocks to persist. As the market cannot clearly predict with accuracy the turning points in the long-term growth of a company, value stocks tend to provide positive surprises, and in consequence outperform the market. LaPorta (1996) found that investors' expectations about future earnings are more than often too extreme; this hypothesis is supported by empirical findings based on the forecasts of American analysts. Stocks with high earnings expectations tend to underperform stocks with low earnings expectations. Similar trends can be observed in current year's earnings estimates, with downward revisions for growth stocks much higher than for the rest of the market. Bias towards growth can be explained by looking at the work in the financial services industry.

In fact, it is easier for an analyst or a broker to recommend growth stocks over value stocks to a portfolio manager as the perceived risk would not be the same; the hypothesis applies in the same manner to fund managers who recommend stocks with liquidity. The idea being that across this chain of participants everyone has to justify him or herself about the investment decisions made.

2.2.1.2 Earnings surprise literature review

The literature on earnings surprise is more recent. For example, Chan et al. (1996) examined whether the forecasted returns based on past returns is due to the market's under-reaction to information; they suggest that this outperformance is the product of an under-reaction by analysts' consensus to earnings surprises. Similarly, Chan and Chen (1991) postulated that the earnings prospects of firms are associated with a risk factor in returns: firms that have poor prospects signalled by low stock prices and high book to market ratios have higher expected returns than firms with strong prospects. Fama and French (1995) tested for a relationship between the risk factors in return and earnings. To demonstrate this relationship they discussed the hypothesis by testing whether or not there are earnings shocks in size and book to market, and tested whether there are traces in returns of common factors in earnings. However, their results were not entirely successful, finding that the market and size factors in earnings do not help to explain the change in returns also no evidence has been reported regarding the book to market factor in earnings; and suggesting that the failure might be partly due to some noisy measures of shocks to expected earnings.

Also, it should be noted that analysts tend to be biased in favour of companies they cover due to some pressure from the management of those companies and are thus less reluctant to downgrade their estimates following a negative surprise than to upgrade them following good news. For example, Bernard and Thomas (1989) studied whether there is an explanation for post-earnings drift and explained that the price response to new information is delayed.

This delay might occur because there is a lack of available information to be assimilated or because certain costs such as transaction costs exceed gains from an immediate exploitation of the information. Another explanation is attributed to a misspecification of the CAPM[27] and a failure to adjust abnormal returns fully for risks. Chen and Zhang (1998) examined whether the behaviour of value stocks is the same across different countries such as the US, Japan, Hong Kong, Malaysia, Taiwan and Thailand. To examine this, they classified firms by size and book to market and identified the risk associated with value firms (e.g., dividend is used to analyze the financial distress of a company, financial leverage to measure the financial risk and earnings uncertainty to

[27] The capital asset pricing model is used to determine a theoretically appropriate required rate of return of an asset. The CAPM was introduced by Jack Treynor, Willam Sharpe, John Lintmer and Jan Mossin independently working on the earlier work of Harry Markowitz on diversification and modern portfolio theory.

measure the future cash flow risk) and showed that value stocks offer considerable returns in the US, Japan, Hong Kong and Malaysia as a compensation for risk; results are not similar in Taiwan and Thailand because the spread of risk between firms is too small. The given reason for the results as exposed by Chen and Zhang(1998) is due to some pattern of different maturity of market growth rates in the different countries. For example, the US is more likely to contain a high proportion of distressed companies due to a stable and mature market, whilst high growth markets such as Thailand and Taiwan will have more firms benefiting from the expanding economy and therefore the risk attached to those firms is less high than the one attached to a mature company where investors are uncertain about the outlook. The authors argued that higher returns for value stocks are compensation for risks.

Frankel and Lee (1998) examined analyst earnings forecasts to see whether or not they are useful to predict the cross section in stock returns in the US. They used consensus earnings forecast as a new benchmark for market expectations about future earnings and found that analysts tend to be over-optimistic in firms with higher past sales growth and higher price to book ratios; also, they showed, by contrast, that cross-sectional errors in three-year-ahead consensus forecasts are predictable. Dechow and Sloan (1995) found no evidence that stock prices reflect extrapolation of past trends in earnings and sales growth; however they found that a contrarian strategy can be used when looking at future earnings growth based on analysts' forecasts. Ou and Penman (1989) compared the ability of price and financial statement to predict future earnings and found that financial statement is a good predictor of future expectations.

Similarly, Lev and Thiagarajan (1993) identified a set of financial variables to be useful in examining firms and examined further the relevance of those variables over earnings, also called the L-score, which has proven to be highly correlated to the F-score. Recently, Piotroski (2012) has looked at the source of return differential for value/glamour stocks and tested whether the prices of glamour (value) firms reflect overly optimistic (pessimistic) expectations.

In summary, a more dynamic approach would imply the use of multiple pieces of information contained in the financial statements.

Before introducing the literature review on the different uses of the F-score, we would like to introduce survivorship bias. One frequently raised problem in the discussion of value investing is the question of survivorship bias. The main idea is that heavily discounted stocks are more likely to disappear than the market in general as the result of bankruptcy or an acquisition. Thus, some value stocks which have disappeared are no longer present in most databases. It is said that survivorship bias would lead to an overestimation of the outperformance of value stocks. When analyzing data it is therefore essential to include companies which are no longer listed. Another way of minimizing the survivorship bias is to limit one's universe to larger companies, where the influence of this effect is less likely to arise. Chan et al. (1994) provide evidence on the existence of bias in the pricing of value and glamour stocks.

2.2.2 Literature review regarding the F-score

2.2.2.1 F-score literature review

By examining fundamental statements, Piotroski (2000) developed a composite called the F-score to distinguish winners from losers in a market and help investors seeking returns. The model is measured as the sum of nine binary signals.

When building the F-score, Piotroski suggests using four profitability measures: 1) Return on asset (ROA[28]), 2) Cash flow from operations (CFO[29]) and 3) Δ ROA (current year less prior year). ROA is calculated as net income before extraordinary items divided by total assets whilst CFO is cash flow from operations divided by total assets. If ROA is positive the firm is said to be profitable, so the firm scores one, otherwise it gets zero. The same notion is applied to CFO. Also, in order to improve the profitability, Piotroski looked at the variation in ROA (Δ ROA) by simply looking at the year-on-year change in ROA. If the current year ROA is greater than the previous year, the firm is awarded a score of one, zero otherwise.

The model compares net income before extraordinary items against cash flow from operations, 4) if the change in CFO is greater than the change in ROA then the firm scores one, otherwise it gets zero. As mentioned in different papers, most notably by Sloan (1996), who showed that earnings driven by positive accruals[30] earnings (i.e., profits are greater than cash flow from operations) is a bad signal about future profitability and returns. Sloan examined further the nature of information contained in accruals and cash flow to see if the information is reflected in the price, and stated that "Firms with relatively high (low) levels of accruals

[28] A manager often measures the performance of a firm by the ratio of income to total assets (income is usually defined as earnings before interest but after taxes). This is an indicator of how profitable a company is relative to its total assets and gives an idea of how efficient management is at using its assets to generate profit. In this research we use net income before extraordinary items, which represents the net income before being adjusted by extraordinary items such as accounting change, discounted operations, extraordinary item, and taxes on extraordinary items.

[29] Cash flow from operations does not include long-term capital or investment costs, also called operating costs. Cash flow can be calculated as = EBIT + Depreciation – Taxes.

[30] On a balance sheet, an expense or asset that is recognized before it is paid. Accruals are recorded as liabilities or non-cash-based assets. These accounts include accounts payable, accounts receivable, goodwill, future tax liability and future interest expense.

experience negative (positive) future abnormal stock returns that are concentrated around future earnings announcement” (p. 290, *Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?*).

In his demonstration, a main idea is highlighted by the fact that investors are “fixated” on earnings and therefore will tend to overprice or under-price stocks in which the accrual component is relatively high or low; this situation occurs when earnings are not fully anticipated.

Sloan (1996) found that someone who will build a strategy of buying low levels of accruals and shorting stocks which are reporting relatively high accruals will achieve a return of 10.4% over a year, as demonstrated by Sloan (1996). Chan et al. (2007) investigated whether analysts, when predicting an earnings announcement, adjust their estimates either in favour of a company or to help managers. They argued in their article that recent US market conditions have increased the predisposition of analysts towards positive earnings surprises. The results accentuate the fact that non-negative surprises are less likely to happen in growth stocks rather than in value stocks.

Overall, they examined how the stock markets react to earnings surprises and whether this growing attitude is more pronounced with growth stocks than with value stocks. The results concluded that analysts have a predisposition to incentives and therefore are influenced in the way they manage earnings and forecasts with the goal to please investors. With regard to this attitude, analysts are becoming “cheerleaders” in the way they recommend stocks. Potential bias in earnings surprise as analyst are becoming cheerleaders.

Also, Piotroski identified three factors that would help avoid stocks running into financial difficulty: an increase in leverage, deterioration in liquidity or the use of external financing are assumed to be bad signals about financial risk. Leverage is the annual change in a company’s long-term debt, as measured by the year-on-year change in the ratio of long-term debt to total assets. The ability to self-finance a business particularly given the current turmoil in debt markets is important and more often than not forgotten at the peak of an economic cycle.

By raising external capital a firm is showing its inability to generate sufficient internal funds. As demonstrated by Myers and Majluf (1984), if a firm has to issue common shares to raise part of all the cash required to finance an investment project this is perceived as a negative sign by investors. The three possibilities that emanate from their articles are that a firm can finance an investment by issuing stocks, reducing its cash balance or even selling marketable securities. As stated by Myers and Majluf “The conventional rational behaviour behind holding slack (cash liquid assets or unused borrowing power) is that the firm does not want to have to issue stock in short notice in order to pursue an investment opportunity" (p. 134, *Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have*). "Slack does not allow a firm to take advantage of investors by issuing only when the stocks in undervalued: if investors know the firm does not have to issue to invest then an attempt to issue sends a the wrong signals to the market " (p. 195, *Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have*). In fact, an attempt to issue if there is no need sends a wrong signal to the market.

The results of their findings sum up the different ways for a firm to issue when it comes to investment decisions and are expressed below as they can be useful for investor decisions:

- It is better to issue safe securities than risky ones. Firms should go for bonds when they want to raise capital.
- Firms can build up slack by restricting the issuing of dividends; another way would be to issue stock when manager's information advantage is small, otherwise stock price will fall.
- Firms should not pay dividends if at a later stage they have to raise funds by issuing risky securities.
- A merger can help to increase the combined value of a slack. In addition, an increase in long-term debt is likely to place additional constraints on the firm's financial flexibility.

Regarding the leverage/liquidity, Piotroski defined the 5) variable as FT_LEVER as equal to one (zero) if the firm's leverage ratio fell (rose) in the year preceding portfolio formation. Piotroski is also concerned with short-term debt denoted as 6) Δ Liquid; the measure concerns the short-term financing of the business and is measured as the annual change in the current ratio (ratio of current assets to current liabilities). A rise in the current ratio indicates the ability of the company to service debt costs, whilst a decline could indicate potential short-term problems.

Ikenberry et al. (1995) examined long-run performance stocks following open market shares repurchase announcements for the period 1980 to 1990 and found that, for the results of undervaluation, value stocks experience average abnormal returns for a buy and hold strategy during four years of 45.3% whilst for growth stocks the repurchase of stocks is less likely to be of the same importance. The authors explained that a company might repurchase shares due to capital structure adjustments, takeover, signalling, excess cash distributions, and substitutions for cash dividends. When discussing why management might choose to repurchase shares, the most common answer from managers is undervaluation of shares and that their shares represent a good investment. Despite this fact, the author's discussed that the information behind share buyback is largely ignored by market participants; indeed, only 3.5% of them react to shares repurchases. According to them, high book to market stocks that announce share buyback are more likely to be truly out of favour stocks. As discussed by Lakonishok et al. (1994), not all high book to market firms are true out of favour firms. (True out of favour firms will show higher average returns compared with high book to market firms in general.)

Also, the work of Michaely et al. (1995) analyzed when a firm is initiating the payment of a cash dividend or omits such a payment, signalling a change in the corporate policy. They have investigated the three-day reaction to initiation or omission announcements over the long term and found that announcement initiated with omission results in a price drop of about 7% and initiations are associated with a price increase of 3%.

A hot topic at the moment is rights issues or seasoned equity offerings, unless the shares are given away for free, in which case this might not be considered as a rights issue; issuing stock costs the existing shareholder either in cash and/or in dilution. See for instance Loughran and Ritter (1995), who issued an article which examined companies issuing stock from 1970 to 1990. The analysis compared companies issuing "IPO" (initial public offering) and "SEO" (seasoned equity offering) and whether or not those companies underperform companies that are not-issuing stocks for five years after the offering date. Their results showed that firms issuing stocks from 1970 to 1990 either through an IPO or SEO have been poor long-run investments for investors. They found that the average annual return during five years after issuing is only 5% for firms going through an IPO and 7% for companies going through SEO. In contrast, someone who would have invested in a non-issuing firm would have produced an average annual return of 12% per year for an IPO and 15% for SEO.

A deeply discounted rights issue at depressed prices might be irritating for shareholders given that many companies currently raise funds by issuing buyback stocks several months earlier at a significantly higher level. In his model, Piotroski defined the 7) EQ_OFFER as equal to one, zero otherwise if the firm did not issue common equity during the year of the portfolio formation for those stocks that issue equity. It is measured as the year-on-year change in shares. Piotroski highlights "The fact that these firms are willing to issue equity when their stocks prices are likely to be depressed highlights the poor condition that those firms are facing" (p. 9, *Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers*).

Finally, Piotroski looked at the operating efficiency designed to measure changes in the efficiency of the firm's operations. The model includes two simple measures of the firm's operating margin, 8) Margin, which measures the year-on-year change in gross operating margin and the annual change in the asset turnover; and 9) Turnover, which shows how much sales increased relative to the size of the asset base. Increasing sales at a greater speed to the change in asset base implies that a firm is generating more business from existing assets rather than simply making acquisitions.

Thus, F-score is the sum of the individual binary signals, **F-score = F_ROA + F_CFO + F_ΔROA + F_ACCRUAL + F_ΔMARGIN + F_ΔTURN + F_ΔLEVER + F_ΔLIQUID + EQ_OFFER.**

For each year from 1976 to 1996 in the US equity market, Piotroski calculated the market value of equity, and book to market ratio at fiscal year-end. After removing all the financials for each fiscal year, Piotroski ranked all firms with sufficient data on Compustat to identify book to market quintiles and size terciles. According to Piotroski, historical data represents both the best and most relevant information of a firm's financial condition. Across his review, Piotroski applies tests to his strategy, firstly by comparing the returns earned by a high F-score firm against the ones earned by a low F-score, and secondly the test compares a high F-score firm against the complete portfolio of all high book to market firms. The results were tested using t-statistics as well as implementing a bootstrapping approach to test the difference in portfolio return. The findings show that the mean return earned by a high book to market firm can be increased by at least 7.5% annually through the selection of strong high book to market firms.

The success of this strategy is based on the ability to distinguish firms that will have high future performance and the market's inability to highlight them, which gives an edge to an investor. In addition, Piotroski showed that a strategy that buys high F-score and sells low F-score will lead to a 23% annual return and the strategy appears to be robust across time. Among the different limitations described by Joseph Piotroski, we were able to find the potential data snooping bias when matching Compustat with CRSP when it comes to match the return, plus the translation of the different factors into binary signals could potentially eliminate useful information. Thirdly, Piotroski documented that less than 44% of all high book to market firms earn positive market-adjusted returns in the two years following the portfolio formation.

2.2.2.2 G-score literature review

Mohanram (2005) analyzed whether applying a simple, financial-based statement analysis to a high and low book to market sample can help an investor to shift its return. By looking at financial statements, Mohanram aimed to extrapolate earnings and future cash flow profitability. Relevant signals are aggregated into a single composite, also called the G-score, which consists of separating winners from losers in a universe of low book to market stocks.

The G-score consists of a set of eight criteria, tested to identify winners from losers among low book to market firms in terms of ex-post stock returns from 1978 to 2001. The sample is partitioned in a variety of ways in order to tackle the problem related to implementation, and results are strong among the entire partitioned sample including large firms, firms well followed, firms with put options and firms with a high level of liquidity. However, as mentioned by Mohanram this mitigates the potential to implement a long-short strategy.

Those signals are all created using financial statements. Mohanram defined the earnings variability measured as the variance of a firm's ROA, and sales variability as the variance of a firm's year-over-year sales growth looking at quarterly financial statements over the past four years and adding the constraint that at least six quarters' information is available. In the case where data are missing, the observations are not deleted but the signal is denoted as zero.

The signals/variables used in this paper to separate potential winners from losers in a low book to market universe of stocks are classified into three categories: traditional fundamentals, variables relevant to a firm's profitability and cash flow performance. Firms that are currently profitable are likely to remain profitable and maintain their financial strength over the long term. Profitability is measured in two ways, firstly by the ROA, defined as the ratio of net income before extraordinary items scale by average total assets; and secondly by comparing the ROA of a given firm to the ROA of all other low book to market firms in the same two-digit SIC code (defined by Compustat). Thus, G1 is equal to one if a firm's ROA is greater than the median ROA for all low book to market firms in the same industry and zero otherwise. Mohanram used an additional measure of profitability by calculating ROA with cash from operations instead of net income as used by Piotroski (2000). Mohanram defined the second signal, G2, as equal to one if a firm's cash flow ROA exceeds the median for all low books to market in the same industry and zero otherwise. Sloan (1996), among others, has shown the importance of accruals by demonstrating that, generally, firms with greater accruals components in their earnings are more likely to underperform in the future. Accordingly, G3 is defined as equal to one if a firm's cash flow from operations exceeds net income and zero otherwise. G4 is defined as equal to one if a firm's earnings variability is less than the median for all low book to market firms in the same industry and zero otherwise. G5 is defined as equal to one if a firm's sale growth variability is less than the median of all low BM firms in the same industry and zero otherwise. When defining these variables, Mohanram mentioned that he was focusing on sales growth rather than earnings growth, as it is more difficult to conceptualise negative earnings, which many low books to market have.

The final three growth signals are based on the different actions that a firm may take to boost future growth, such as R&D, capital expenditure and advertising. A high level of expenditure on those items may boost future growth and make the firms more likely to meet market expectations. Accordingly, G6, G7 and G8 are defined as equal to one if a firm's R&D, capital expenditure and advertising intensity are greater than the medians of the corresponding variables for all low book to market firms in the same industry and zero otherwise. The intensity of R&D, capital expenditure and advertising are measured by deflating these variables by beginning assets.

Firm level return is calculated using CRSP as a buy and hold return for 12-month and 24-month horizon starting on the 1st of May of the year after the portfolio formation to ensure that the most recent variable is included in the financial statement. Returns are size adjusted by subtracting the return in the same period for the same capitalization decile[31]. In some extent, investors can argue that the G-score is preferable to the F-score when applied in the context of growth stocks.

Mohanram's results are consistent with his findings that when financial statements are appropriately designed to analyze growth stocks the strategy is good at distinguishing ex-post winners from losers. To emphasize his findings, firms with the lowest G-score earned a mean-adjusted return of 3.1% in the first year after portfolio formation, while firms with the lowest G-score earned 17.5%, meaning that a long/short strategy based on G-score might help an investor to earn abnormal returns. As mentioned by Mohanram "Ability to short is crucial to use this strategy" (p. 134, *Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis*).

Finally, Mohanram found strong results in firms without analyst following, consistent with the findings of Piotroski (2000) that the success of the F-score is driven by investors ignoring the financial information of particular firms. The only downside of using this strategy, as pointed out by the author, is that most returns are earned on the downside and therefore being able to short stocks is "crucial".

[31] A method of splitting a set of ranked data into 10 equally large subsections. This type of ranking is commonly used among the literature studies in finance.

2.2.2.3 Discussion about the use of the F-score in the US stock market

Woodley el al. (2011) found that financial statement variables identified by Piotroski (2000) no longer distinguish between future winners and future losers when applied to a high book to market environment. The purpose of their research was to see whether the ability of the F-score to distinguish companies has diminished, disappeared or improved. Following a methodology described by Piotroski (2000), for each fiscal year each firm's book to market ratio and total market value are calculated. When information was missing from Compustat, the authors decided to drop that observation from the sample, and the process is repeated for each fiscal year from 1976 to 2008. Thus, they grouped all observations given a specific F-score and year for the purposes of determining the return. Then the same tests were rerun after separating the sample into two sub-samples; the first one is for fiscal years ending in 1976-1996, in order to match the sample proposed by Piotroski (2000), and the second sub-sample is for the period of fiscal years 1997-2008.

Firms were then sorted into quintiles based on their book to market ratios and separately sorted into terciles[32] based on size. Each firm that falls within the top book to market quintile is considered part of the sample of value firms. Raw returns and market-adjusted returns were then calculated for the one-year period beginning in the fifth month after the end of fiscal year T. Woodley et al. (2011) also tested for market risk and F-score to see whether the average excess market-adjusted return for the high F-score can be potentially explained by differences in the average beta measure. Their results showed that it cannot be explained by a higher average level of beta.

For the period as a whole and for the sub-periods, high book to market firms tended to have smaller returns and be less profitable than the average firms. Indeed, the results show that, during the period that falls into Piotroski's sample period, the strategy of investing in high F-score will produce an average market-adjusted return inferior than the one produced by investing in a broad portfolio of value stocks, and suggest that results produced by Piotroski (2000) were in fact inverted for the period 1996-2008 despite the fact that results for the period 1976-1996 confirm Piotroski's findings that higher F-score leads to higher return. The mean one-year market-adjusted return to high F-score stocks is 23.71% lower than the return to the overall set of value stocks and 26.52% lower than the return to low F-score firms. Both results are statistically significant at the 1% level and appear to be economically significant.

[32] A way of dividing the sample into three parts.

Overall, they performed twelve tests; high F-score firms underperform in ten of these twelve comparisons. As a point to take away from this, the strongest underperformance occurs when the point of comparison is the mean return.

Even if Woodley el al. (2011) found that the F-score is no longer useful for portfolio construction due to different findings then the one reported by Piotroski we highly believe that the strategy is useful at distinguishing between winners and losers. It's difficult to describe the rational behind their findings but one possible assumption could be the risk characterisation at that time for firms was not the same; also the market was facing economic downturn where the volatility is increasingly becoming one potential major explanation on their results. The F-score is useful and has proven to be useful at distinguishing winners from losers otherwise that kind of strategy would not be use anymore by hedge funds or funds when forming their investment ideas.

2.2.2.4 Discussion about the use of the F-score and the G-score in the Thai stock market

Tantipanichkul (2011) extended the research proposed by Piotroski (2000) and Mohanram (2005) to see whether those two scores can help an investor to distinguish between winners and losers in the Thai stock market. The author used three categories of composite scores: the F-score, the G-score and a T-score (combination of the F-score and G-score), which is a combination of both traditional and growth-orientated measures. All financials signals were computed for each firm and firms were classified as either good or bad based on their outcome. The sums of all variables were assigned to a composite score within the range of zero to nine. Then the market-adjusted return for each stock for one- and two-year buy and hold strategy was computed. Accordingly, the mean and median were calculated. A portfolio formation occurs in the fourth month after the annual financial statement has been released to ensure that all the information has already been factored to each investor. This paper examines whether accounting based financial analysis can help investors earn excess returns among high and low book-to-market firms in the stock exchange of Thailand and the market for alternative investment during 1994 to 2008.

The investment strategy is then developed by purchasing a group of high F-score and shorting a group of low F-score; then to judge if the strategy is effective the magnitude of the return difference is considered. Tantipanichkul (2011) tests for statistical significance using the T-test and the non-parametric Wilcoxon test. The entire methodology is repeated for the G-score and for the T-score, which is a combination of the F-score and the G-score. The results show that high score firms outperform low score firms both one and two years after portfolio formation. For the F-score, the mean (median) for the high and low group is 24.09% (12.97%) and 5.39% (-3.83%). The G-score yields a lower return with a return difference of 11.44% (16.85%) for the mean (median) market-adjusted return. The second comparison is between the F-score and T-score; the high T-score group earns a mean (median) market-adjusted return difference of 23.60% (26.21%). Overall, a combination of the F-score and the G-score, also called the T-score, leads to higher positive returns.

Regarding low book to market firms, the F-score market-adjusted return has a mean value of 5.38% for the high group, compared to 11.43% for the low group. Similar trends are also seen for the median value with a larger return of 23.64% and results are statistically significant. Using the G-score, Tantipanichkul (2011) showed that on average investors can earn returns of 16.57% and similar trends are seen for the median value: the market-adjusted return has a median of 1.71% for the high group whilst -12.% for the low group, which are both statistically significant. While the returns from the F-score and the T-score outperform those of the G-score, Tantipanichkul (2011) highlighted the ability of being able to short stocks in the low group.

Overall, these findings are consistent with Mohanram (2005), that there exists a unique set of composite scores, and demonstrate that fundamental analysis when suitably modified can also be successful for growth stocks. Moreover, in the high book to market stocks universe the G-score shows more feasibility than the T-score.

In summary, this paper shows that a simple accounting-based strategy can effectively separate winners from losers in terms of future returns. The performance of each score with one- and two-year investment horizons is compared and indicates that, regardless of the composite score used, firms in the high book to market group generate higher market-adjusted returns than firms with low scores. Among high book to market firms the T-score is better able to differentiate financially healthy firms, whilst the author claims that, for low book to market firms, the G-score can produce subsequently higher returns than other composite scores and even when taking short-selling into account it still generates the highest positive return. Overall, the results show that fundamental analysis is quite effective in Thailand, especially among small and liquid high book to market stocks.

2.2.2.5 Discussion about the use of the F-score in the European stock market

Mohr (2012) provided evidence on the utility of the F-score in the growth segment market and back tested a strategy that buys high F-score and shorts low F-score growth stocks while focusing on the Eurozone equity market from 1999-2010, and excluding all companies that do not have sufficient financial data as well as excluding all the financials using data provided by MFIE capital[33].

Mohr excluded all companies that do not have enough sufficient data to calculate price to book ratio and attempted to remove all companies with a trading volume less than EUR 10,000. He then sorted the entire sample into price to book quintiles and extract the 20% with the highest P/B ratio.

A test of high and low F-score growth stocks is constructed referring to an F-score of 0 to 3 as "low F-score" and an F-score of 7 to 9 as "high F-score". The market-adjusted returns for a one-year holding period for both portfolios are compared and calculated as well as the hedge return(high F-score – low F-score) for the strategy by subtracting the low F-score market-adjusted portfolio return from the high F-score market-adjusted return. Portfolios are readjusted once a year, always at the 30th June. For reasons of simplicity, trading costs, slippage and taxes are not taken into consideration. In a second step, Mohr tested whether the results are significantly different from zero and did so by applying a variety of t-tests at different levels of confidence. In addition to the evaluation of hedge return, Mohr controlled for possible other factors that could explain the returns in the growth segment of the Eurozone equity market. Accordingly, a multifactor regression was built, consisting of all the explanatory factors such as size, price to book, momentum, accruals, equity offerings and F-score.

In summary, the results provide empirical findings around strategies that evaluate the power of fundamental analysis within the Eurozone growth stocks. The findings confirm research by Piotroski (2000), who stated that the F-score does not lose its predictive ability when applied to growth stocks. However, the results provide counter-evidence to Mohanram's (2005) results, which provides evidence that fundamental analysis is strongly context dependent and that the F-score loses its predictive ability once it is applied outside the value stocks universe. Additionally, the strategy can be vulnerable in a practical set-up due to the low sample size out of the F-score.

[33] MFIE Capital is an independent organization providing investing tools and media for investors.

2.2.2.6 Discussion about the use of 24 accounting variables in the European stock market

Bird and Casavecchia (2007) used a dynamic model based on 24 accounting variables to predict the probability of a stock having improved earnings per share performance. Their results are consistent with Piotroski's and Mohanram's that fundamental analysis can help differentiate "good" from "bad" value and glamour stocks. They examined single and combined impact on value and growth stocks based on two insights, either sentiment/momentum and accounting fundamentals/financial health. The focus in this paper is on evaluating, within a European market, the use of both market sentiment and financial health to enhance the performance of value and growth investment strategies.

Bird and Casavecchia suggested looking at the combined impact of the application of both sentiment indicator, based on the stock's recent market performance, and a financial health indicator based on several accounting ratios. This is to determine which value stock is better and, to an extent, determine which of these two indicators is more relevant. They suggested the possibility of constructing a well-performing growth portfolio by identifying the sentiment and financial health indicators as already suggested for good-value stocks.

Also, as a final check they applied the three-factor model proposed by Fama and French (1992) in order to analyze the characteristics of value and growth portfolios constructed after applying a combination of market sentiment and financial health indicators. The aim was to establish whether the strategies reflect either a risk-based explanation or returns are reflecting systematic mispricings.

The sample consists of almost 8000 firms from 15 European countries: France, Italy, The Netherlands, Germany, Spain, the United Kingdom, Belgium, Portugal, Ireland, Austria, Greece, Norway, Sweden, Denmark and Finland. The analysis was conducted over 15 years from 1989 to 2004. Data were obtained from Compustat Global Vantage[34]; data for stock indices and other financial variables were obtained from Datastream[35] and GMO UK[36]. The exchange rate effect was avoided by using data expressed in local currencies and, consistent with other findings, the authors excluded all stocks attached to the financial sector and those with a negative book value

[34] A database that provides data on publicly traded companies in more than 80 countries. The database covers 90% of the world market capitalization, including 90% of the Asian market capitalization, 90% of the Indian market capitalization, 95% of the Taiwanese market capitalization and 95% of the European market capitalization.

[35] An extensive database that contains historical financial data. It contains over 40 years of data and data is provided by a number of organizations such as Worldscope, International Monetary Fund, Organization for Economic Cooperation and Development and national government sources.

[36] Global investment management firm that employs more than 550 people worldwide.

or priced at less than a pound. The sample results are constituted of approximately 1650 stocks in each year.

Then, they ranked stocks at the end of August each year based on their sales to price valuation metric and used these rankings to form equally weighted value portfolios to measure performance over a period ranging from one month to 36 months. They decided to classify the top quartile of stocks ranked by sales to price as value stocks and the bottom quartile as growth stocks. Also, they formed portfolios in August to allow sufficient time for the accounting information to be factored in. The returns that they report are excess returns where the benchmark is the return on an equally weighted portfolio of all the stocks included in the sample each month. Then they examined the impact of applying a sentiment screen to both value and growth stocks. They used price momentum over six months as a measure of market sentiment. Furthermore, they divided each value and growth portfolio according to whether the stocks contained in them were classified as winners or losers and observed the performance of four portfolios: value winners, value losers, growth winners and growth losers. Then they calculated the excess return for each of these four groups over a period of one and 36 months.

Accordingly, in order to measure the financial health they developed an indicator based on 24 variables which have previously been founded to be relevant and each year this indicator was used to predict the probability that the reported earnings per share (EPS) for each stock would be greater for the next financial year than in the current one.

The results show that a strategy of identifying value stocks and growth stocks can be overcome by the application of a sentiment/momentum indicator and a financial health indicator. The main problem was to identify when particular stocks will experience a market turnaround. Sentiment proves to be effective for timing the acquisition of these stocks by delaying the entry until a market turnaround is likely to happen. However, for growth stocks timing is difficult as those stocks are already expensive. However, the researchers proved the combination of sentiment and financial health to be very useful in identifying those stocks and provided insights that they are able to extract higher added value from a “good” growth portfolio that they are from a “good” value portfolio.

2.2.2.7 Discussion about the use of the F-score in Emerging stock markets

Hyde (2013) examined the effectiveness of the F-score signal across all countries in the MSCI Emerging markets index and whether the F-score in global emerging markets can distinguish between winners and losers. The results show that there is a meaningful premium attached to high F-score stocks which is unrelated to the size, value and momentum premiums. Hyde (2013) proposed an additional factor, the conditional bias to re-examine the premium attached to high book to market stocks.

After replicating Piotroski's (2000) F-score, the study examined the effectiveness of the F-score signal across all countries in the MSCI emerging markets that can discriminate between high and low returns in emerging markets. The study was carried out over the period January 2000 to December 2001 on the MSCI Emerging Markets Index. The sample contains 667 stocks in January 2000 and 805 stocks in December 2001 and 99,658 stock date observations in total. All portfolio average excess return is equally weighted. If missing data occur, he substitutes the index return for that stock date, then the excess return of a stock is calculated as the absolute total return for the stock less the benchmark return for the country/region to which the stock is assigned. Similarly, when conditioning stocks for size, value and momentum effects, stock are sorted relative to other stock in the same country/region to which the stock is assigned to ensure the portfolio is country neutral. Countries examined in isolation are those which contain many stocks and have a large market capitalization; the other countries are aggregated into countries on the basis of geographic proximity.

Observations of the F-score between 4 and 7 account for 74% of the data sample, while 13% are associated with extreme scores of 0, 1, 8 and 9. The results show that there is little year-to-year variation in the average F-score within the range of 4.89 to 5.66. The average F-score reached its lowest points in the years 2000, 2009 and 2010 due to weak economic growth coinciding with weak financial strength. The Latin America region (excluding Brazil) registered the highest average F-score while South Africa registered the lowest. While some delay in the diffusion of the information into stock prices, it is therefore necessary for the F-score to have predictive power also they argue that the confirmation bias can have a role in data snooping and thus in explaining the cross-sectional variation.

The results do not vary greatly with the value or momentum of stocks. The equal weighted average F-score for the bottom 50% stocks ranked on the price to book ratio is 0.11 lower than for the top 50% stocks, and the average F-score between high and low (six- month) momentum stocks is only slightly higher at 0.21.

In his analysis, Hyde (2013) compared the equal weighted excess return of high F-score ($F \geq 8$) to low F-score stocks ($F \leq 2$). The results show that there a statistically significant premium attached to stock with $F \geq 8$; this premium is 3.51 % per annum and 2.06% for a 12-month period;

however, this is lower than the 7.5% premium observed by Piotroski (2000). The results show that this premium varies within the lowest 20% and for the middle 60% of stocks ranked by price to book.

Regarding the difference between high and low F-score, results are 4.10% per annum for a six-month period and 4.36% for a 12-month period. However, this premium is lower than the 23% per annum premium reported by Piotroski (2000). This analysis was repeated using an F-score ≥ 7 for the high price to book firms and F-score ≤ 3 for the low price to book firms, and the results are slightly better, being 5.28% and 4.94% per annum for the six-month and 12-month holding period respectively.

Over his research, Hyde (2013) tested for components that generate stronger contributions and found that ΔLeverage makes a negative premium to the overall portfolio. Hyde also controlled for size effects and his findings contrast with Piotroski's results that the premium is concentrated among small stocks.

After testing for value premium, findings show that the premium attached to high F-score stocks is higher for value stocks than growth stocks regardless of whether they are defined by P/B or PE ratio. Momentum effect has also been tested and the findings show mixed evidence as to whether the return differential between high book to market firms and low book to market firms is sensitive to changes in momentum.

Findings are consistent with previous evidence from both developed and emerging market studies: stocks with a high F-score earn a significant return premium over stocks with a low F-score. The results indicate that the Piotroski F-score can be implemented into value and/or momentum investing strategies in emerging markets.

Caveats highlight the importance of including new information about the stock price to be necessary for the F-score to have any predictive power. Also, even after allowing for bias effect results, there are still unanswered questions as to whether the low value/low momentum stocks generate a higher premium than low value/high momentum or high value/low momentum stocks. Therefore, a more in-depth analysis of the Brazilian market is also needed.

2.2.2.8 Discussion on the use of the F-score in the Brazilian stock market

Galdi and Lopes (2008) showed that results obtained by accounting-based fundamental analysis strategies in the US cannot be replicated and extended to other markets. One of the main reasons described in their article is the hypothesis that abnormal return to financial statement analysis will be generated by limits in arbitrage and could not potentially be replicated in the Brazilian market as they control for restrictions on the actions of arbitrageurs. This paper tends to replicate the approach developed by Piotroski (2000) using nine signals and making assumptions about the features of the Brazilian market. Galdi and Lopes (2008) classified firms as either "bad" or "good" depending on the signals on future price and performance. If the realization was good they assigned a one, otherwise a zero. The main reason for re-adaptation of the Piotroski model is the absence of published cash flow in Brazil.

The three financials signals used to measure changes in the capital structure and liquidity and cash flow are ΔLiquid, ΔLEVER and EQ_OFFER. Cash flow is defined by firm-year change on cash and cash equivalent scales by beginning of the year total assets. Regarding the use of the debt variable due to the absence in the way Brazilian firms report, they considered long- plus short-term debt as opposed to long-term debt as defined by Piotroski (2000). They decided not to use EBITDA as a proxy for cash flow from operations due to the huge discrepancies in numbers.

The research focused on the Sao Paolo stock exchange from 1994 to 2004 and collected data from the Economatica[37] database: 6682 firms each year after excluding all financials. The findings showed that an investor could have changed its market-adjusted return from one year (two years) from 5.7% (42.4%) to 26.7% (120.2%) by selecting financially strong high book to market firms in the Sao Paolo stock exchange. Overall, the results show that the market-adjusted return is considerably higher than the one constructed by Piotroski (2000) and point out that a strategy consisting of buying and shorting will generate a 41.8% annual return; and the authors concluded that financial statement analysis based on strong high book to market firms can help to distinguish winners from losers.

However, the strategy only works for the groups of small and medium firms and for the groups of low and medium liquidity firms but not for large and high liquidity firms. Therefore, results are mainly driven by small, low liquidity. Also, firms who do not have derivatives based on their shares are making the implementation of the strategy really difficult. Recently, Dosamantes (2013) examined whether an accounting fundamental analysis when applied to the Mexican stock market can contribute to the literature on value investing for investors in Emerging markets. Two scores were constructed, the F-score and the L-score, based on the methodology developed by Piotroski (2000) and Lev and Thiagarajan (1993). Econometric models were designed and performed to show how those two scores add value to book to market ratio, firm size and

[37] Database that offers information listed on the exchange such as for Brazil, Argentina, Chile, Mexico, Peru, Colombia and Venezuela.

earnings per share. Using quarterly data from Economatica for all active firms in Mexico's stock market from 1991 to 2011, a significant relationship was found between the F-score and the L-score, enhancing some evidence of the value relevance of accounting fundamental analysis for investors when forming their portfolios, and contradicting the findings of Galdi and Lopes (2008).

2.2.2.9 Discussion about the use of the F-score in the Indian market

Aggarwal and Gupta (2009) investigated whether a strategy based on accounting fundamentals can help investors to distinguish between winners and losers in the Indian stock market. The strategy adopted is based on the Piotroski (2000) model, using the nine fundamental signals identified to compose the F-score; researchers look at whether this strategy is applicable since there is evidence of market efficiency at a late form in the Indian market. Using Piotroski's framework and applying a different approach to portfolio formation, convincing evidence was found highlighting the hypothesis that a fundamental analysis-based investment strategy can separate winners from losers in the Indian stock market. The research was carried out for the period of financial year ending 2003 to financial year ending 2007. On the 31st March 2004, all the companies listed on the National Stock Exchange were arranged in descending order of book to market ratio using the CMIE[38] database *Prowess*[39]. Then the book to market firms were divided into five quintiles; focusing on the high book to market quintile 104 companies came out of the poll. Accordingly, three portfolios were developed, denoted as P1, P2 and P3; each portfolio consisted of companies having an F-score in the range of 0-3, 4-6, 7-9. Furthermore, each portfolio consisted of 20 equally weighted companies randomly selected from the respective F-score groups.

Returns were calculated on a buy and hold basis for a period of one year and two years and portfolios were formed three months after financial year-end, so that all the information required was available. Market-adjusted return was calculated in two forms, according to the authors, calculating absolute excess return over the market returns and by calculating returns as driven by risk of the portfolio. For market-adjusted return three market indices were used as a benchmark (S&P CNX Nifty[40], CNX midcap[41], and S&P CNX 500[42]).

[38] Centre for Monitoring Indian Economy.

[39] Largest database of financial performance of Indian companies.

[40] Is the National Stock Exchange of India's benchmark for the Indian equity market. The CNX Nifty covers 22 sectors of the Indian economy and offers investment managers exposure to the Indian market.

[41] Is a benchmark for midcap segment; the CNX Midcap index represents about 12.41% of the free float market capitalization of the stocks listed on the National Stock Exchange of India as on 30th September, 2013.

[42] Represents about 96% of total market capitalization and about 93% of the total turnover on the National Stock Exchange of India.

The results showed that firms in the highest book to market quintile have a mean (median) book to market ratio of 4.96 (3.51). Descriptive statistics regarding the nine fundamental signals out of the F-score were also performed among the three portfolios suggesting the number of positive signals was higher in portfolio 3 (F-score above 7), indicating that investing in companies with high book to market can be profitable.

Also, a comparison of portfolios on different fundamental signals was evaluated, plus the performance of the three portfolios over one year and two years was observed. Overall, portfolios 1 and 2 showed a mixed response in terms of excess performance out of the three market indices; however, portfolio 3 was consistent in its performance with all the market indices outperformed for both one- and two-year windows. This finding highlights the ability of the F-score in creating subsequent returns.

2.2.2.10 Discussion on the use of 11 fundamental variables in the US stock market

Xue and Zhang (2011) examined whether institutional investors exploit abnormal returns derived from financial statements and studied how transaction costs and arbitrage risk affect the profitability of the trading strategy. Finally, they studied the impact of institutional investors' trading behaviour on the profitability of the fundamentals-based trading strategy.

To focus on institutions that are more likely to trade on fundamental signals they followed Bushee's (2001) findings. For instance, Bushee (2001) examined whether investors exhibit preferences for near-term earnings over the long term and whether this has an impact on stock prices. One of the main assumptions is that managers boost operational and accounting decisions to boost short-term earnings under the pressure of institutional investors referring to the term "myopic". Findings show that the strongest institutions favour firms with short-term earnings rather than firms with long-term earnings. A suggestion might be that clients are more interested in short-term returns.

Across the literature three categories of institutions are defined: transient, dedicated and quasi-indexers. Findings highlight that Xue and Zhang (2011) expect transient institutions to be more likely to trade on fundamental signals, and also the empirical results hold after controlling for other factors that may affect institutional investors' trading decisions such as analyst forecast revisions and post-earnings announcement drift.

Additionally, Xue and Zhang's (2011) found that association of future abnormal returns and fundamental signals increases with transaction cost and arbitrage risk. The final part of their analysis examined whether institutions trading on abnormal returns using financial statements have an impact, and in this they made progress by suggesting that transient investors tend to reduce abnormal returns associated with fundamental signals. The results suggest that institutional investors' trading helps alleviate the market under-reaction to information contained in fundamental signals and improve market efficiency.

Throughout their analysis, they examined 11 financial ratios that measure a firm's profitability, operating efficiency and liquidity, and many of their fundamental signals concur with those in Piotroski (2000). However, in contrast with Piotroski, who is looking at only distressed firms, Xue and Zhang (2011) chose fundamental signals to describe the financial conditions of ordinary listed firms, and therefore included financial ratio that are most visible to investors. One difference between their fundamental signals and the one highlighted by Piotroski is that their measures are all industry adjusted whereas Piotroski's ratio are benchmarked against zero. Another difference is that they do not include equity issuance and change in leverage ratio in their selection signals. These ratios are intended to measure changes in capital structure and a firm's ability to meet future debt obligations.

Therefore, each fundamental signal is assigned a score of one if the ratio is above its industry average in that year, indicating a positive signal about the firm's outlook, or a zero otherwise. The industry average for each year is calculated using only firms' 31st December fiscal year-end and industry years with fewer than five observations are deleted. All the 11 signals are aggregated into an F-score following the same observations made by Piotroski (2000). To verify if the F-score has the power to predict future abnormal returns, they constructed an equal weighted investment portfolio each year. The results showed that, of the 22 years from 1982 to 2003, this trading strategy of buying high F-score and shorting low F-score generated positive market-adjusted returns in 18 years, with the average three-month (nine-month) market-adjusted returns of 2.78% (7.62%). The annualized markets adjusted buy and hold returns are around 12%, which is lower than those documented by Piotroski of 23%.

Lastly, they checked for robustness, calculated alternative measures of abnormal returns such as size-adjusted return and size, market beta, book to market and momentum-adjusted return and tested statistically.

Regarding the data sample, they collected information data from Compustat industrial and research files, return data from CRSP monthly stock database for NYSE, AMEX and NASDAQ firms and institutional investment data from institutional investors. The analyst coverage and forecast data are obtained from the summary file of the IBES database. Firms' years missing any of the 11 fundamental signals as well as financial service and utility firms were excluded from the sample. The final sample was 2026 unique companies.

Then, they examined firms' market-adjusted buy and hold return over a three- and nine-month horizon starting from 1st April after the previous fiscal year-end. As an alternative of abnormal return measures, they calculated size-adjusted return and four-factor-adjusted returns. Size-adjusted return is defined as the raw return less the return of the portfolio of the firms in the same size decile.

Overall, they found that fundamental signals derived from publicly available financial statements have the power to predict future stock returns. This paper looked at abnormal returns by examining the trading behaviour of sophisticated investors, i.e., transient investors, and found that transient investors trade on fundamental signals. This finding is consistent with the explanation that the stock market under-reacts to financial statement information and that sophisticated investors take advantage of this arbitrage anomaly. The authors further explored role and limits to arbitrage and found that abnormal returns to fundamental signals increase with arbitrage cost – transaction cost and arbitrage risk. They provide documentary evidence that transient institutions' trading and holdings help the stock market more quickly impound information contained in fundamental signals into stock prices.

In summary, the results suggest that the F-score has the power to predict future stock returns and a fundamental analysis based on the F-score can earn abnormal returns.

2.2.2.11 Discussion to see if the F-score can be used to predict institutional investor demand

Choi and Sias' (2010) goal was to develop a new test to see whether gradual incorporation of information contributes to the relationship between financial strength and subsequent returns. Using the F-score return model, Choi and Sias are able to contribute to the literature by showing that the F-score also predicts institutional investor demand, and their results are consistent with previous findings.

The authors took a different approach as to whether or not financial information and strength forecast institutional demand. The method requires the calculation of all variables required for building the F-score at the end of each fiscal year, after removing all financials.

Also, they are screening for stocks with a CRSP share code of 10 or 11 and add two criteria: firm has to have at least $25 million market capitalization and book to equity of at least $12.5 million.

After carrying out the above, they partitioned the sample into three components: the portion attributed to future institutional demand as a proxy for expectations under the gradual incorporation of information, the portion attributed to future profitability as a proxy for expected profitability under the risk based explanation, and the portion unexplained either by future institutional demand or future profitability as a proxy for all other explanation; then they examined the relationship between F-score and each of the three future return components under different statistical tests.

Using quarterly data from Compustat plus institutional ownership data over the period 1983 to 2006, Choi and Sias (2010) suggested that institutions that trade actively to maximise short-term profits are responsible for driving prices long after the release of the information captured by F-score.

Also, they found that the gradual incorporation of information explanation accounts for 25% of the relation between the F-score and future returns and the risk-based explanation accounts for 75%. Their results showed that the gradual incorporation of information and risk-based measures fully explained the relationship between the F-score and abnormal return.

Solely, this test assumes a linear relation when assessing F-score and the method assumes that the change in market expectations and subsequent return is fully captured by institutional demand.

As a conclusion, this chapter has demonstrated the use of the Piostroski F-score in our current environment providing all the literature related to the context i.e. the different market (universe) where the F-score or an alternative to the F-score has been used. This enables us to apply the Piostroski F-score strategy to our universe and establish the novelty of our work by using a new approach when forming the F-score.

2.3 Data and methodology

2.3.1 Where did we decide to collect the data?

We decided to collect the data from the Standard & Poor's Compustat North America database and from the CRSP US stock database, which provide both fundamentals data and returns on all listed NYSE, Amex and NASDAQ common stocks. The Standard & Poor's North American data is unique in the sense that it is standardized to ensure comparability by removing reporting variability and bias to ensure that comparability exists among similar types of data. Data are collected from shareholders' reports, 10-K reports and other reliable sources. Items include, as an example, annual and quarterly income statement, balance sheet, cash flow data, company name. The CRSP US stock database provides a unique research source; it includes CRSP's unique identifier, allowing for clean and accurate backtesting analysis.

To extract data we used SAS under a Linux[43] server where we created a table to extract all the variables required to build the Piotroski screen from Compustat identified by global company name. Each fiscal year from 1991 to 2012, data are extracted for the S&P 1500. We excluded all financials using the SIC codes[44] provided by Compustat. In order to avoid survivorship bias, stocks that were delisted during the period were also included. The sample contains 38,855 observations in total.

Using SAS, the first step was to identify the appropriate "Mnemonics" for the company annual fundamental data group; the more key mnemonics specified the narrower the scope. We created a table where we requested the global company name denoted as "gvkey" included in the S&P 1500. Also, variables such as "Datadate" can be requested to define the period, such as fiscal year-end data.

Extracting the data from specific data items enables the researcher to focus on the research, and learning about SAS as a programming language is certainly something that can benefit a later career.

2.3.2 Building the F-score

When it comes to building the F-score, we followed Piotroski (2000), which comprises nine fundamentals signals to distinguish winners from losers in a universe of stock. (Please refer

[43] An operating system.
[44] Four-digit numerical codes that identify a company's primary business. A company's primary business is the industry from which the company derives its greatest revenue.

to the literature review regarding the choice of the different variables by Piotroski.) The model consists of a set of binary financial tests based on the profitability, leverage, liquidity and operating efficiency. The more tests a stock passes the better the investment is said to be. So a stock that passes all the tests out of an F-score of nine would be an excellent stock whilst a stock with a score of zero or one should be avoided. For every test the company passes it receives a one; in the case it fails in the test the company is assigned a zero. The maximum score a firm can be assigned is nine, meaning that the company has improved on all the metrics since it last reported. When we extract company variables we look for the last fiscal year-end period updates. Any stocks that score seven or above can be bought in the portfolio; the following year the test is re-run and the company that is no longer performing regarding the new variables just drops out of the portfolio. Later we test for the data migration and the stability of the F-score in order to understand the likelihood of the models and the volatility in the scores. Therefore, a company will stay in the portfolio as long as it keeps the momentum on beating its previous result in the range of seven to nine.

2.3.2.1 Profitability

Firstly, regarding the profitability the model uses four profitability measures: i) ROA, ii) CFO and iii) Δ ROA. ROA is calculated as net income before extraordinary items divided by total assets, whilst CFO is cash flow from operations divided by total assets. If ROA is positive, the firm is said to be profitable and the firm scores one, otherwise it gets zero. The same notion applies to CFO. Improving profitability is done by simply looking at the year-on-year change in ROA where we let year be fiscal year applied to all our variables. If the current year ROA is greater than the previous year, the firm is awarded a score of one, zero otherwise. iv) If the change in CFO is greater than the change in ROA then the firm scores one, otherwise it gets zero. See for instance Sloan (1996), who shows that earning driven by positive accruals is a bad signal about future profitability and returns.

Four profitability measures are considered: i) ROA, ii) CFO, iii) ΔROA and iv) CFO > ROA

2.3.2.2 Leverage, liquidity and the source of funds

Piotroski identified three factors that would help avoid stocks running into financial difficulty and each of them is used today in an investor's assessment. For instance, the three variables are leverage, liquidity and the source of funds, the v) Δ Leverage is the annual change in a company's leverage as measured by the year-on-year change in the ratio of long-term debt to total assets, vi) Δ Liquid concerns the short-term financing of the business and is measured as the annual change in the current ratio (the ratio of current assets to current liabilities). A rise in the current ratio potentially indicates the ability of the firm to service its debt costs, whilst a decline could potentially indicate some short problem financing. vii) Δ Finance is measured as the year-on-year change in shares outstanding; the company scores one if the number of shares outstanding is no greater than a year ago, zero otherwise.

Three balance sheet measures are considered: v) Leverage, vi) Liquidity and vii) Finance

2.3.2.3 Operating efficiency

The model includes two measures of the firm's operating efficiency, i.e., an increase in operating margin denoted as viii) Δ Margin is measured as the year-on-year change in the gross operating margin; the firm scores one if the full year margin is greater than the previous one, otherwise zero. And the annual change in asset turnover denoted as ix) Δ Turnover is measured as the year-on-year change in turnover; the firm scores one if the percentage increase in sales exceeds the percentage increase in total assets, zero otherwise. This shows how much sales have increased relative to the size of the asset base. An increase of the sales at a greater speed to the change in asset base implies that a firm is generating more business from existing assets rather than simply making acquisitions.

Two operating efficiency measures are considered: viii) Margin and ix) Turnover

Thus, the composite F-score is the sum of the nine variables described as:

F-score = F_ROA + F_CFO + F_ΔROA + F_ACCRUAL + F_LIQUID + F_ΔLEVER+ F_ΔFINANCE + F_ΔMARGIN + F_ΔTURN.

2.3.3 Calculation of portfolio return

We measure firm return on a year buy and hold return; the process starts by extracting all the companies with a high F-score comprised from 7 to 9. We expect these firms to have the best performance given the outcome of their fundamental analysis. This approach leads to a sample of 4780 observation from 1991 to 2012. CRSP monthly returns are used to compute cumulative returns over three, six, nine and 12-month intervals to calculate efficiently the compounded returns on a rolling basis as of the end of every month; to produce an output we expect each common stock to have monthly records without any gaps. This way, for each rolling window, the preceding 12 records will contain missing or non-missing returns information during the last 12 months.

CRSP monthly returns and Compustat sample are linked using the CRSP-Compustat Merged Product (CCM); however, the macro can produce inaccurate matches, leaving a bias when it comes to match the two identifiers. **(Aware of the potential bias, we follow the process.)**

The macro CRSP/Compustat Merged Database includes Standard & Poor's Compustat data, reformatted into CRSP's proprietary CRSP Access database format, plus additional data tables that map the CRSP permanent company and security identifiers (PERMCO and PERMNO) to Compustat permanent company identifier (gvkey).

A common misconception is that CCM is CRSP stock market data merged with Compustat accounting data. In fact, CCM contains only Compustat data items, but can be searched by CRSP's "PERMNO" or PERMCO in addition to Compustat "gvkey". The link tables are then merged. Solely for different reasons the researcher can be faced with incomplete matching results from the fact that the CRSP database covers stock prices on public stock exchange while Compustat does not require a company to have a traded stock. Another issue could be that there is a disagreement between CRSP and Compustat over which is the surviving company and, finally, the match between Compustat (gvkey) and CRSP (Permno) is not one to one. For example, a company might have multiple equity issues.

If a security has been removed from the exchange, CRSP calculates a delisting return of this security by comparing the security's value after it delists with its price on the last day of trading. In fact, the code accounts for possible delisting events such as bankruptcies, mergers and acquisitions, liquidity. Incorporation into the total buy and hold returns would help to avoid biases that would arise from the exclusion. For each stock, returns are compounded over various time intervals relative to the fiscal period end date specific to this company. The market return follows the same procedure and can be used to derive the excess return for every stock.

2.3.4 Data migration methodology

This section tries to describe the methodology used to perform a trend-following data approach which is part of our analysis regarding the stability and volatility of the Piotroski F-score across time. Using probability when assessing the task, the first step is to plot the actual observed numbers of F-score by year and form a basket of stocks that will remain in the sample across time.

The purpose of this analysis is to explain in percentage how the Piotroski model is volatile and how the outcome of the F-score is changing over time. In fact, market turbulence and rising doubts about the duration of the current environment have increased investor interest in lower risk and higher quality stocks.

2.4 The data analysis

2.4.1 Data migration and stability of the F-score over 1995 to 2012

We present the approach developed in the section above. The sample is constituted of 516 stocks each year from 1995 to 2012.

Table 2.4-1 Performance of all the 516 stocks from the migration over 1995 to 2012

Piotroski score in year "t+1"

Piotroski score in year "t"

1995-2012	0	1	2	3	4	5	6	7	8	9
0	25.0%	8.3%	8.3%	33.3%	0.0%	8.3%	0.0%	8.3%	8.3%	0.0%
1	5.7%	2.9%	8.6%	25.7%	20.0%	11.4%	11.4%	5.7%	8.6%	0.0%
2	1.5%	0.8%	8.3%	11.3%	13.5%	15.8%	22.6%	18.0%	8.3%	0.0%
3	0.0%	1.8%	4.5%	8.3%	14.4%	23.2%	24.3%	16.8%	6.7%	0.0%
4	0.1%	0.5%	1.7%	5.9%	16.6%	26.1%	27.7%	16.0%	5.0%	0.4%
5	0.0%	0.3%	1.2%	5.6%	14.9%	27.8%	29.0%	15.6%	5.2%	0.4%
6	0.0%	0.2%	0.7%	5.0%	16.5%	28.8%	26.7%	16.4%	5.3%	0.4%
7	0.1%	0.1%	1.2%	4.2%	16.5%	28.1%	28.1%	15.6%	5.4%	0.7%
8	0.0%	0.0%	1.3%	7.1%	17.6%	30.2%	29.6%	9.2%	4.5%	0.6%
9	0.0%	0.0%	0.0%	5.1%	28.2%	28.2%	25.6%	7.7%	5.1%	0.0%

Table 2.4-1 shows the entire migration probability sample for 516 stocks; this is simply the number of times each F-score appeared; the probability is expressed as a percentage and is calculated by dividing a frequency by the total frequency and multiplying by 100. Please note that we let F-scores 0, 1, 2, 3, 4, 5, 6, 7, 8, and 9 be described as "F-1, F-2, F-3, F-4, F-5, F-6, F-7, F-8, and F-9" when it comes to giving an explanation of the graphs or charts.

This gives us a record of past outcome and an understanding of possible trend – a trend being the general movement in the data over time. If someone can understand past changes over time in the F-score then that same person/investor can consider ways of projecting these forwards and using such a projection as a measure for future forecasts in the likelihood of the F-score.

An investment company might be particularly interested in the change of the F-scores when it comes to buy one of them. We can describe the relationship using a straight line of probabilities. Consider the following example: where an investor is interested in the volatility over time of an F-score of F-9. If we bought a stock with a score of F-9 the chances that it stays an F-9 the following year are null; however, the investor has an 8% chance that the score becomes an F-7 and therefore stays in his portfolio. Of course, when analyzing those figures, the investor should be careful as those F-scores might be influenced by a range of factors including the economic wisdom. The figures do, however, provide a useful guide. Overall, it can be expected that the high F-score decreases over time whilst an increase can be viewed in the bottom F-score. Taking another example, an investor who buys a stock rated an F-7 in the F-score is likely to have a 16% chance of this stock remaining an F-7; however, he has a 0% chance of the stock becoming an F-0.

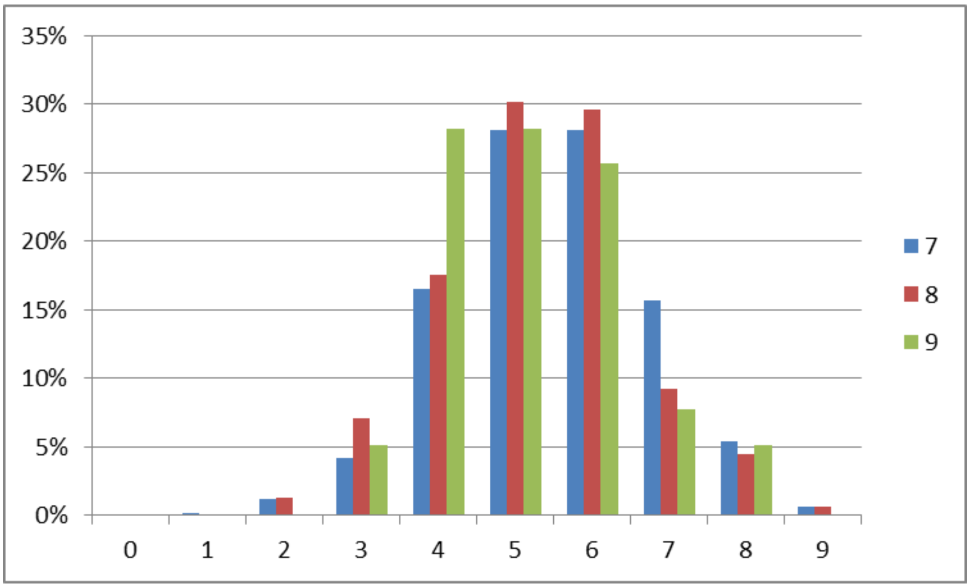

Figure 2.4-1 High F-score change. The histogram displays the distribution of the F-score by showing for each corresponding F-score the probability expressed in percentage

This histogram in Figure 2.4-1 appears to have almost a perfect bell-shaped pattern: there are more data in the middle and less towards the two extremes, suggesting that the assumption of normality in the future can be tested using t-test.

This histogram displays the change in a high F-score from 1995 to 2012 for a high F-score to become an F-5 or an F-6. In this way the histogram displays the entire distribution of the high F-scores. From this histogram we can see as well the low probability for a change in a low F-score (i.e., from F-0 to F-2). When we look at the shape of the F-7 the distribution appears to be almost normally distributed with the same probability for an F-score of F-7 to become an F-6 or F-5, as figures show the probability is 28% respectively. Also, an investor has an approximately 16%

chance for the F-7 to stay the same or 17% that it becomes an F-4. However, when looking at the F-8 we cannot draw the same conclusion as there is a 9% chance for the F-8 to become an F-7 and an approximately 18% or double chance for the F-8 to become an F-4. Overall, interesting conclusions can be draw out of this histogram. Also, please note the likelihood of the F-9 to become an F-4, an F-5, and an F-6 is approximately the same, around a 28% chance, meaning there might be some stability before the stock loses all its value.

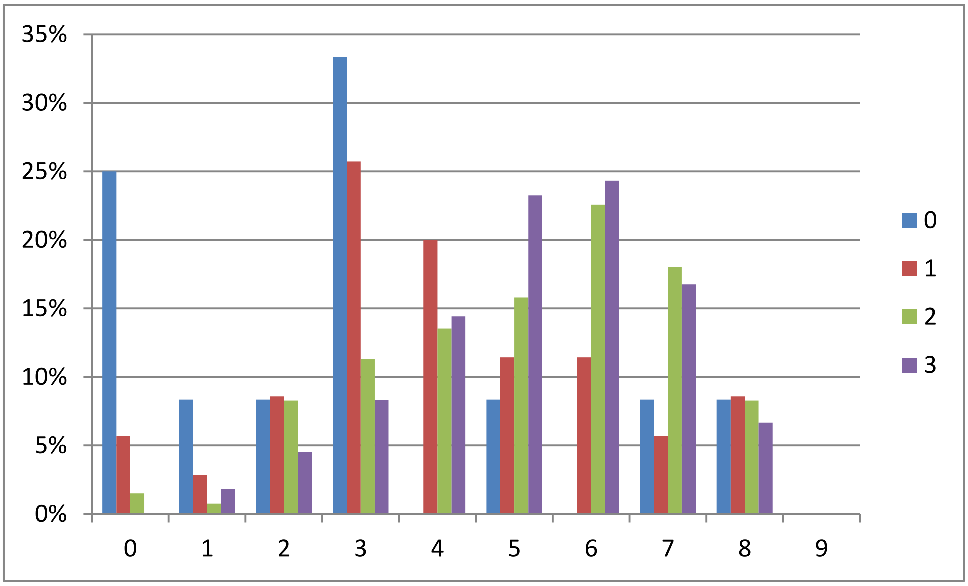

Figure 2.4-2 Low F-score change. The histogram displays the distribution of the F-score by showing for each corresponding F-score the probability expressed in percentage

This histogram in Figure 2.4-2 displays the change in a low F-score from 1995 to 2012, for an F-0 to become an F-3. From this histogram we can see the absent probability for an F-0, F-1, F-2, and F-3 to become an F-9, meaning that the F-score is quite stable. The ability of the F-2 and F-3 to grow gradually should also be noted; a better picture will be displayed and discussed later. The linear upgrade in percentage chance can be seen in F-3, F-4, F-5, and F-6 when looking at those two scores; also, the same gradual decline is apparent in F-7 and F-8.

In the histogram, it is also worth noticing the constant 8% chance for F-0 to become F-1, F-2, F-5, F-7, and F-8. As well, interestingly, the histogram is showing the absence of probabilities for F-0 to become either an F-4 or F-6, which might signify something perhaps when we run some econometric tests – those two scores might reveal another picture. Also, it is worth looking at the likelihood of F-3; indeed, the null probability chance for an F-3 to become F-0 can be seen, implying the idea that an investor interested in using an F-3 strategy has to screen in stocks rated F-1 to benefit from the potential upgrade over time.

Additionally, when looking at F-1 an investor has the same chance for F-1 to become either F-0 or F-7 with a 6% chance for each of them; the same observation can be applied for F-1 to become F-2 or F-8 with a 9% chance.

Figure 2.4-3 shows the migration of an F-score of 2 and 3 for the period 1995 to 2012; as discussed in the previous paragraph, the idea is to get a clearer picture. The y-axis represents the percentage chance that this occurrence appears. The percentage change for both F-scores grows gradually for an F-score of 2, 3, 4, and 6 with a corresponding fall in F-7 and F-8; this growth can be explained by some predominance for those two scores to gradually change over time, particularly the ability for those two scores previously rated as poor investment, due to them showing some ability to continuously improve the prospects of the firms. Some investment strategy might be interesting to develop out of this figure. The percentage chance for F-2 and F-3 to become an F-7 or an F-8 is respectively 18% (8%) for F-2 and 17% (7%) for F-3. In contrast, the ability to become an F-6 is respectively 23% for F-2 and 24% for F-3. The decline after F-6 might be seen as a signal for a sell when buying an F-2 or F-3. Also, the ability to become F-9 for both of those two scores is null, meaning that buying an F-2 or F-3 will lose all its power after being upgraded as an F-8. As spotted earlier, the chance for F-3 to become F-0 is null.

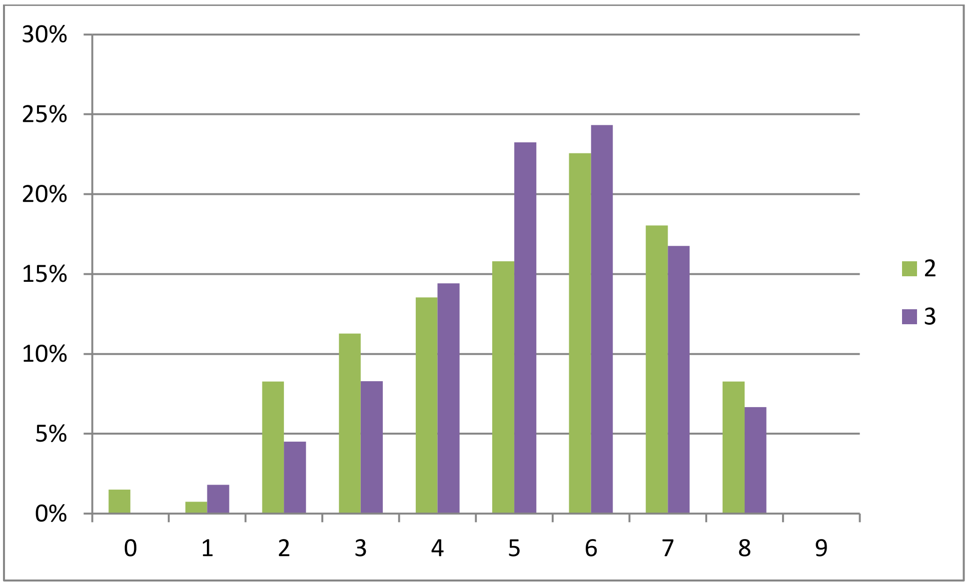

Figure 2.4-3 F-score of 2 and 3 change. The histogram displays the distribution of the F-score by showing for each corresponding F-score the probability expressed in percentage

As described earlier, here in Figure 2.4-3 we have a clearer picture of the outcome of an F-score of F-2 or F-3 in our migration stability, highlighting some interesting pictures, as buying both of those two scores could lead gradually to a potential upgrade of the score, implying an eventual investment opportunity.

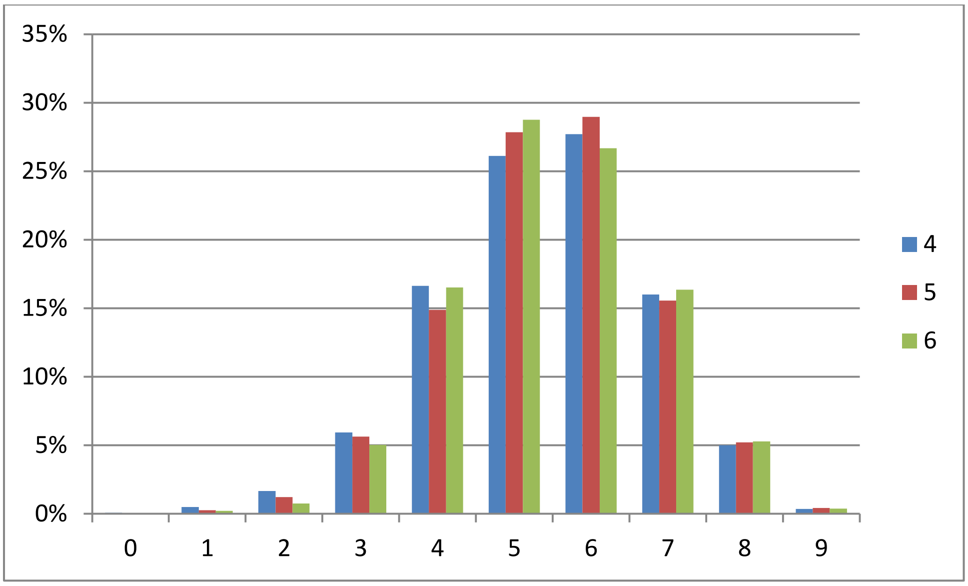

Figure 2.4-4– Medium F-score change. The histogram displays the distribution of the F-score by showing for each corresponding F-score the probability expressed in percentage

When examining Figure 2.4-4, it can be seen that the histogram is centred around an F-score of F-5 to F-6, the values vary from 15% to 30% and the shape of the distribution is quite normally distributed, which means that when an investor buys a score of F-5 to F-6 it has approximately the same chance to go either to the right or the left of the tail.

The centres and spreads are not too different from the high F-score histogram in Figure 2.4-4 but the shape appears to be slightly right skewed, while the high F-score appears to be left skewed with less probability on the F-9 and F-8. Please note the ability for F-4, F-5, and F-6 to become either F-3 or F-8 or F-4 or F-7, describing a bell shape. Also noticeable is the absence for F-4, F-5, F-6 to become F-0.

Overall, these histograms provide an easy to understand summary of the distribution of the F-score migration.

2.4.2 Evolution of F-score return year by year

Here we present a table where we compute the return for each F-score between the various years for the period 1994 to 2012 and compare the results by plotting different graphs in order to get a better idea of the trend in each F-score. Table 2.4-2 gives a comparative insight of the return, which describes the evolution of the return throughout the period. An investor would expect to see all the negative returns located in the low F-scores and all the positive returns in the high F-scores. This table shows, in fact, the potential investment return for a one-year holding period for each individual score. At the bottom of the table, the reader will find the number of companies in each score for the whole period.

Table 2.4-2 – Return of all the F-scores individually over the period 1994 to 2012 fiscal year-end

	fo	f1	f2	f3	f4	f5	f6	f7	f8	f9
2012	-28.20%	-32.17%	-0.06%	13.82%	15.41%	17.50%	17.44%	22.46%	31.83%	8.95%
2011	-43.16%	-41.98%	-5.99%	0.61%	-0.41%	1.78%	9.35%	10.18%	15.63%	3.90%
2010	-0.04%	-0.61%	5.79%	19.91%	15.76%	24.79%	29.41%	30.28%	31.69%	13.89%
2009	-36.40%	-13.01%	24.36%	34.21%	25.68%	39.76%	44.68%	56.95%	71.02%	-7.18%
2008	-55.75%	-58.72%	-45.88%	-32.03%	-34.59%	-30.84%	-26.40%	-21.54%	-9.67%	-24.71%
2007	-28.22%	-32.98%	-11.13%	2.29%	-5.58%	1.56%	10.60%	14.01%	25.68%	15.22%
2006	-28.43%	-15.08%	-9.88%	4.89%	10.69%	16.92%	16.04%	21.84%	30.65%	49.23%
2005	-28.37%	-13.24%	-2.44%	6.81%	5.67%	8.04%	18.12%	29.41%	36.40%	36.32%
2004	-40.12%	-13.89%	-1.76%	10.50%	13.60%	15.08%	26.06%	28.76%	35.33%	69.61%
2003	25.66%	23.76%	39.45%	46.27%	37.88%	41.90%	40.58%	55.47%	59.67%	24.99%
2002	-63.44%	-52.48%	-47.79%	-27.14%	-24.10%	-12.80%	-5.18%	-3.55%	-6.48%	11.93%
2001	-5.82%	-11.56%	-15.85%	7.62%	2.40%	7.33%	19.46%	35.33%	14.08%	38.45%
2000	-33.17%	-8.78%	1.34%	18.84%	8.02%	14.19%	28.47%	24.83%	60.33%	94.24%
1999	16.70%	30.37%	47.04%	26.25%	0.90%	8.17%	14.79%	34.87%	63.47%	53.78%
1998	-10.03%	-12.64%	-6.53%	-2.79%	-5.32%	2.50%	5.38%	12.55%	30.66%	37.87%
1997	-26.11%	-8.88%	4.68%	22.87%	20.15%	24.10%	33.44%	32.25%	49.17%	48.05%
1996	-18.32%	-19.05%	-5.13%	7.76%	7.96%	14.46%	22.44%	26.95%	42.04%	21.15%
1995	-8.77%	0.22%	-0.87%	24.59%	19.69%	22.91%	29.67%	43.08%	38.06%	42.20%
1994	-40.47%	-8.80%	-20.50%	-0.24%	-6.23%	1.63%	4.56%	3.98%	11.54%	69.72%
No of firms	347	525	1045	4144	4419	7188	6805	3844	1207	105

Here in Table 2.4-3 is a summary statistic of the average, median, maximum and minimum for each F-score. When looking at the average and the median number it can be seen that they coincide with the expectations that an investor is looking for. As demonstrated, investors should expect the minimum average return to be in F-0 whilst the highest average return should be located in F-9 with F-0 average return equal to -23.57% and F-9 average return 31.98%. The same story can be highlighted when looking at the median where F-0 equals -28.29% and F-9 median return equals 36.32%.

Also, when taking a deeper look at the maximum and minimum, if someone had bought stock rated as F-0 they would have achieved a maximum return of 25.66% across all those years and a minimum return of -63.44%, whilst if investing in stock rated as F-9 an investor would have earned 94.24% across all those years and a minimum return of -24.71%. All of this shows once again the ability for the Piotroski model to earn abnormal returns when applied to a universe of stocks. There is strong evidence that the greater the quality of a stock as judged by its F-score the better the return.

Table 2.4-3– Average, Median, Maximum and Minimum Metrics

	F0	F1	F2	F3	F4	F5	F6	F7	F8	F9
Average	-23.57%	-15.24%	-2.69%	9.74%	5.66%	11.53%	17.84%	24.11%	33.22%	31.98%
Median	-28.29%	-13.01%	-2.44%	7.76%	7.96%	14.19%	18.12%	26.95%	31.83%	36.32%
Max	25.66%	30.37%	47.04%	46.27%	37.88%	41.90%	44.68%	56.95%	71.02%	94.24%
Min	-63.44%	-58.72%	-47.79%	-32.03%	-34.59%	-30.84%	-26.40%	-21.54%	-9.67%	-24.71%

The Correlation matrix in Table 2.4-4 of the F-score return is computed into what is known as the correlation coefficient, which ranges between -1 and +1. This table gives us a better understanding of the correlation between the different f-scores. A perfect correlation implies that as one of the f-score return moves either up or down the other f-score will move in the same direction. If the correlation is equal to 0 the movements of the f-score are said to have no correlation. In this table the lowest correlation is between F-9 and F-0. When incremented by one, i.e., F-0 and F-1 or F-1 and F-2 or F-2 and F-3 or F-3 and F-4 or F-5 and F-6 or F-6 and F-7 or F-7 and F-8, the correlation is high, proving the upgrade in the financial health of the company; however, when looking at F-8 and F-9 the story is slightly different with a correlation of 0.34.

Overall, all the F-scores are highly correlated, indicating the f-score is capturing gradually the return earned by companies.

Table 2.4-4– Correlation matrix of the return between the different f-scores

Correl	fo	f1	f2	f3	f4	f5	f6	f7	f8	f9
fo	1									
f1	0.86	1.00								
f2	0.76	0.84	1.00							
f3	0.72	0.82	0.91	1.00						
f4	0.59	0.67	0.76	0.93	1.00					
f5	0.57	0.68	0.77	0.93	0.98	1.00				
f6	0.52	0.66	0.74	0.92	0.95	0.97	1.00			
f7	0.66	0.75	0.82	0.94	0.91	0.93	0.94	1.00		
f8	0.57	0.74	0.90	0.89	0.79	0.81	0.83	0.83	1.00	
f9	0.18	0.52	0.22	0.28	0.23	0.20	0.30	0.21	0.34	1.00

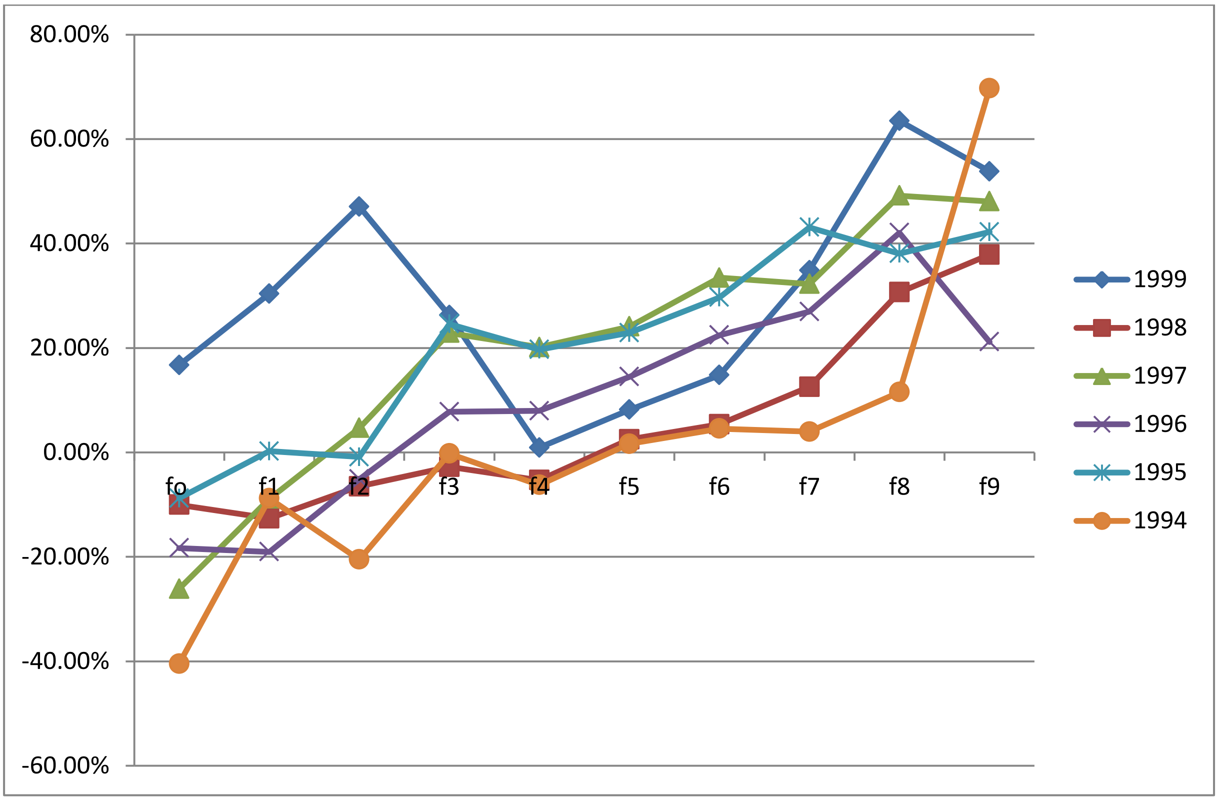

Figure 2.4-5– Covering the period 1994 to 1999, evolution of the F-score return

The graph in Figure 2.4-5 plots the return for the different F-scores from 1994 to 1999. This graph measures how the F-score return change over time. The x-axis of this graph shows the nine f-scores over the period 1994 to 1999 while the returns in percentage appear on the y-axis. It might be seen that the f-scores rose steadily to the F-8 after significantly dropping when it comes to the F-9, especially for 1996.

Overall, the data is generally increasing over time despite a few irregularities that we try to highlight in this paragraph. For example, when taking a deeper look at 1999 it appears that F-4 displays one of the lowest returns, around 0.90%. Also F-0, F-1, F-2, and F-3 are all positive when one should really expect negative returns from these scores, reflecting some possible economic downturn.

Also, when looking at F-9 there is a general decrease in the return – excluding for the following years 1994, 1998, and 1999 – with the lowest return in 1996 for F-9 at 21.15%.

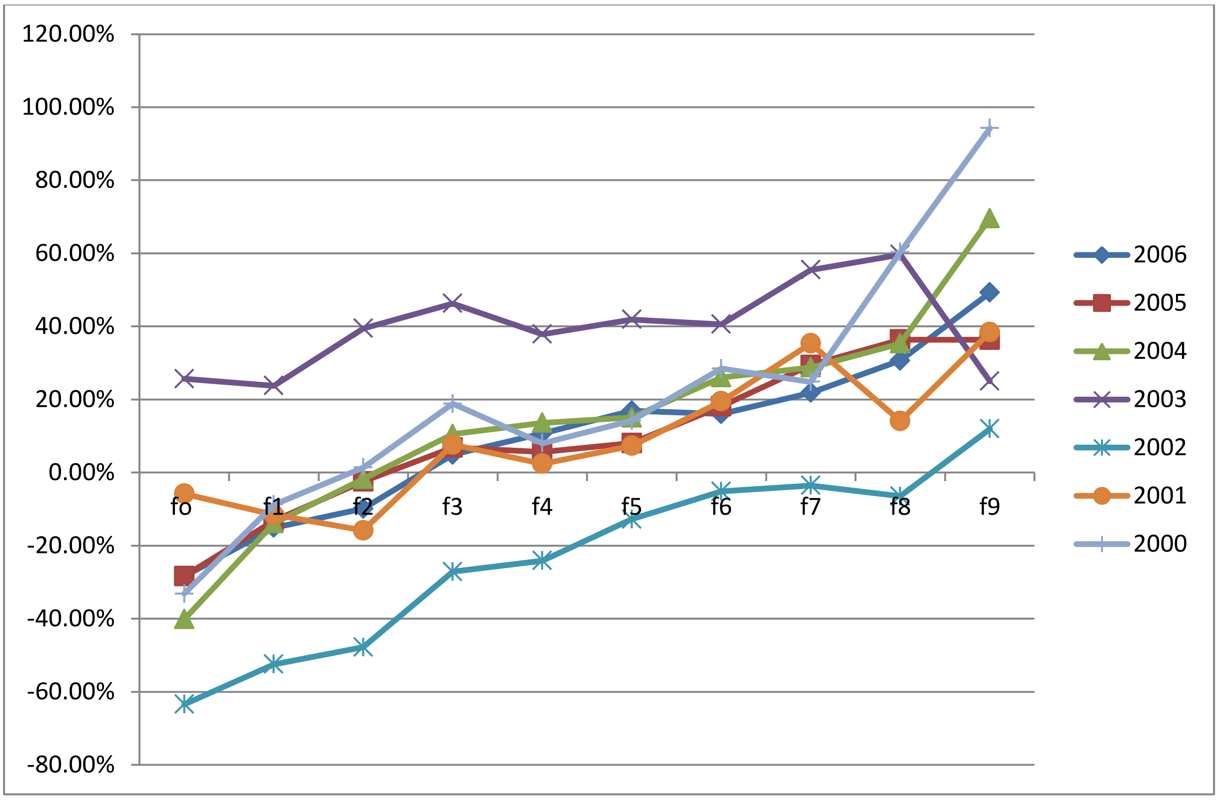

Figure 2.4-6– Covering the period 2000 to 2006, evolution of the F-score return across time

The graph in Figure 2.4-6 shows the trend in the F-score return for the period 2000 to 2006. It can be noticed that there is a poor performance return of F-score in 2002 where only F-9 is positive. Also, some observations can be made when looking at 2003. All the F-scores are positive when really one should expect the picture to be negative for F-0, F-1, and F-2. Accordingly, F-9 is the lowest one after looking at 2002, perhaps highlighting some economic slowdown. Overall, there is a steady growth in the return for 2000, 2001, 2004, 2005 and 2006, even if in 2001 a drop in the return of F-8 can be noticed.

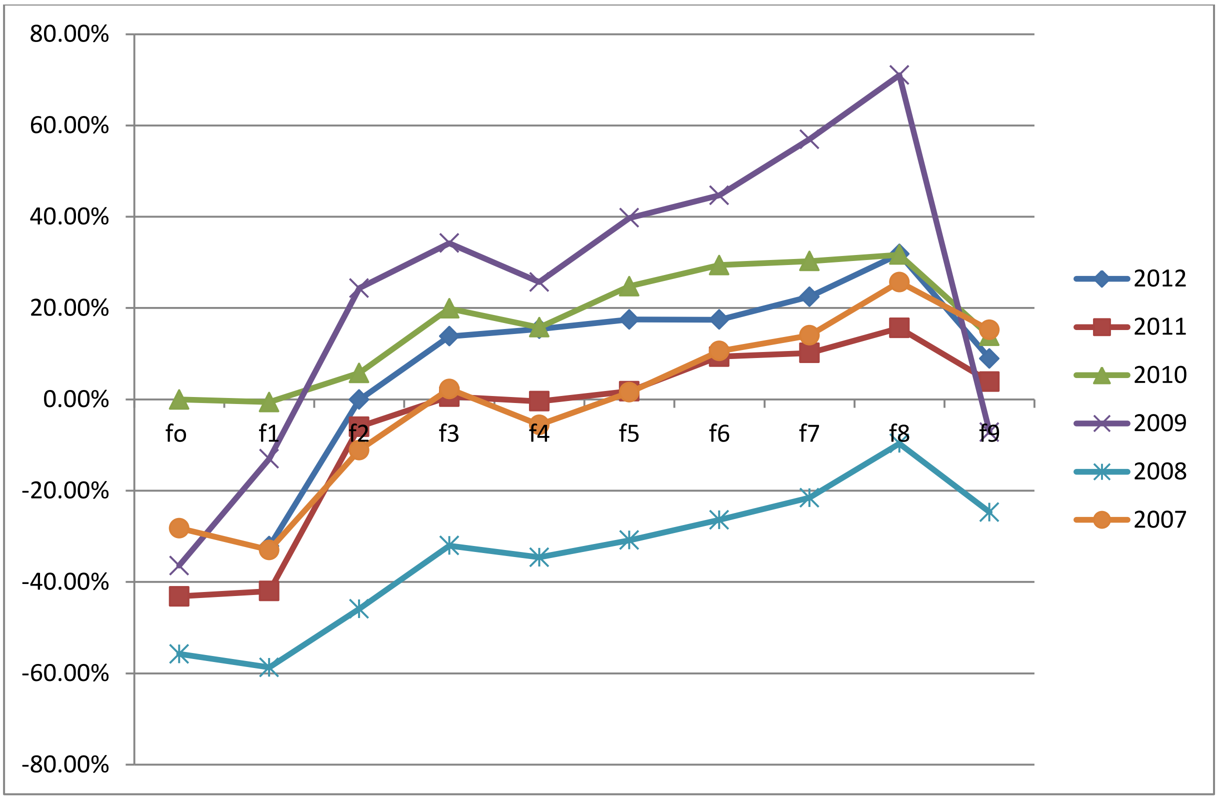

Figure 2.4-7 Covering the period 2007 to 2012, evolution of the F-score return across time

The graph in Figure 2.4-7 shows the trend in the F-score return for the period 2007 to 2012. It can clearly be seen that overall there is a large increase in the trend in all F-scores despite a general decrease in the F-9 for all the years. This indicates this criterion might contain information on future performance or likelihood of the market, as if it did not we should expect a continual increase in the f-scores.

The returns for the following f-scores have continuously risen over the different time periods. In 2008 the trend in the f-score is continuously increasing even if the line for all the f-scores is showing negative return, reflecting the downturn of the economic crisis. 2008 is the worst-performing return line in the graph, with the highest return in 2008 being achieved by an investor buying stocks rated F-8; the return is -9.67%. When looking at the F-9 in 2012 it might be possible to say that 2012 is in a recovery state as the return earned out of an F-9 is better than in 2008, 2009 and 2011; however, it is slightly lower than in 2010 and 2007.

Also, another point to note is that 2010 is the only period where the f-score for F-0 and F-1 return is the lowest compared to any other years. Interestingly, the highest return is achieved in 2009 with the F-8 at 71.02% following a massive drop in F-9, reinforcing the idea that economic downturn could have to be highlighted when looking at this picture. It is also worth noting that for all those periods there is a decreasing return in the F-4 when following a better performance in F-3. That might be in line with intuitive economic reasoning, as the market completes its adjustment to earnings surprises at this time.

2.4.3 Portfolio analysis given by a high F-score: F-7, F-8 and F-9

Table 2.4-5 presents the performance of a buy and hold strategy when an investor buys stock in the basket of high f-score as defined by F-7, F-8 and F-9. The strategy appears to be robust across time.

When it comes to the measurement of investment performance, an investor who pays someone to actively manage a portfolio with the hope of achieving superior performance usually requests the return that he is actually obtaining out of the market. The essential idea behind return measurement is to compare the returns using a portfolio of high F-score with those of a benchmark. In this case we measure the differential returns. Table 2.4-5 describes the performance return for the period 1994 to 2012; the first column give an insight of the return earned by a portfolio based on high F-score (where F-score is greater than or equal to 7); the next column gives the market return for the S&P 1500 over the period covered and, finally, the last column gives investors the excess return in values when forming this strategy.

Table 2.4-5 Portfolio returns and market return for a buy and hold strategy looking to buy into high F-score

Year	Return F-score 7-9	S&P 1500 Market return	Excess Returns against benchmark
1994	6.08%	0.68%	5.40%
1995	42.00%	33.73%	8.28%
1996	31.16%	21.14%	10.02%
1997	37.06%	31.71%	5.35%
1998	18.57%	19.17%	-0.60%
1999	42.73%	23.29%	19.45%
2000	37.66%	-5.47%	43.13%
2001	30.14%	-12.88%	43.02%
2002	-4.20%	-19.97%	15.77%
2003	55.79%	30.29%	25.50%
2004	30.99%	12.79%	18.19%
2005	30.79%	9.95%	20.84%
2006	23.93%	15.00%	8.93%
2007	16.55%	8.15%	8.40%
2008	-19.67%	-33.77%	14.09%
2009	58.98%	28.58%	30.39%
2010	30.43%	17.69%	12.74%
2011	11.12%	2.87%	8.25%
2012	24.52%	15.42%	9.10%

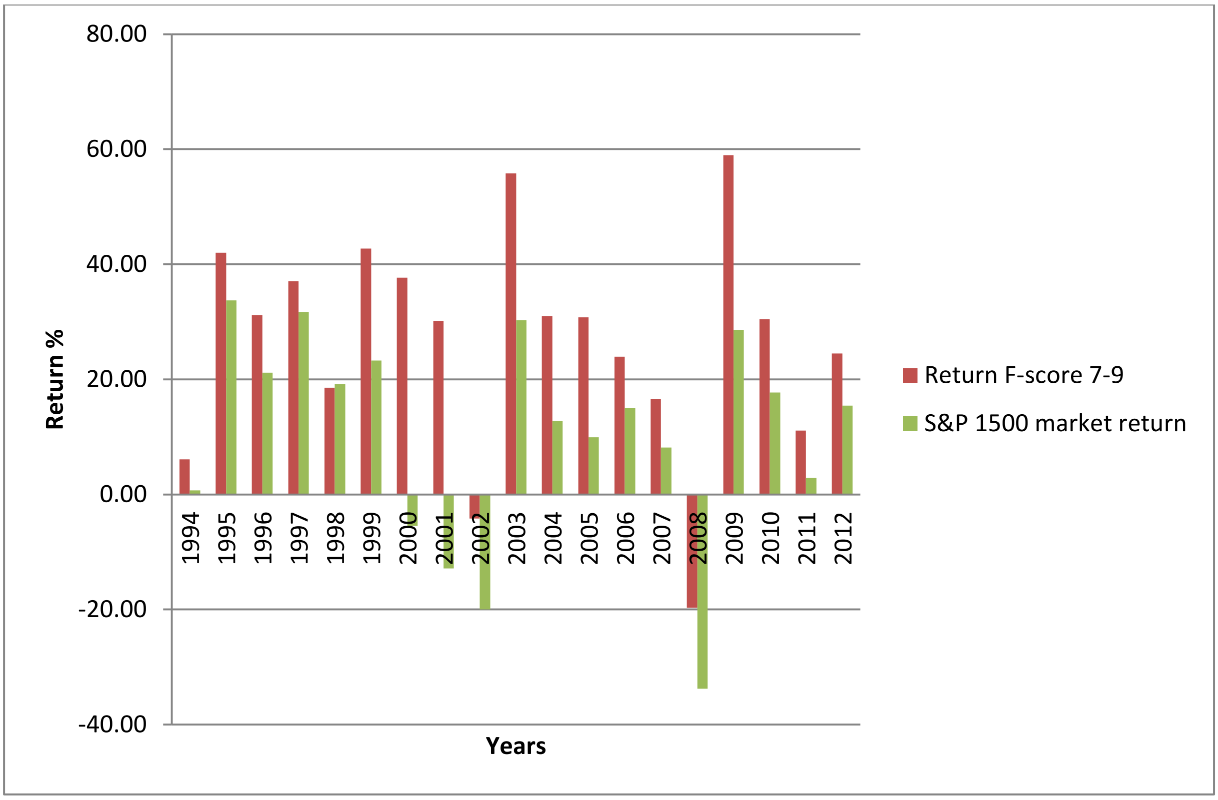

Figure 2.4-8 Performance of the portfolio displayed in a histogram

Figure 2.4-8 documents one-year market-adjusted returns by fiscal year compared to a benchmark (the S&P 1500); the portfolio is taking a buy and hold position in high F-score (F-score greater than or equal to 7).

The portfolio offers the exposure of a well-diversified US company. As stated, the portfolio is benchmarked against the S&P 1500 excluding financials and aims to outperform this over the long term. Also, we are not accounting for any cash in the asset allocation just for the purpose of the demonstration but a deep insight of portfolio analysis would be interesting to develop. The worst performance of the portfolio is in 2008, probably due to the crisis, where the portfolio underperforms by -19.67%; the second-worst performance is in 2002 where the return is -4.20%, reflecting the stock market downturn of 2002. Interestingly, the best performances are achieved following those two crises within 2009 a performance of 59.98% and in 2003 the portfolio return is 55.79%, reflecting that the strategy might perform better after the turmoil where investors lose confidence and therefore do not know into which company they should put their money. The portfolio is calculated on an equally weighted basis and compared to a value-weighted benchmark in order to simplify the analysis **(including dividends)**.

The portfolio is up 24.52% versus the S&P 1500 up 15.42% over the last 12 months in 2012 and in 2008 the portfolio was down -19.67% versus -33.77%, still beating the market. We believe the return tends to come from stock selection, proving its efficiency as the portfolio tends to outperform the market – excluding 1998 where the market return is 19.17% versus 18.57% for the portfolio constituted of high f-scores. Clearly the portfolio, despite avoiding picking poor stocks due to its ability, has been better at limiting downside risk. In 2011 the portfolio returned 11.12%, outperforming the benchmark return of 2.87% by 8.25%.

Investing in high-quality companies that can differentiate themselves from the competition will help investors to outperform in most market conditions since the portfolio is driven by stock selection. Also, from this figure we believe the portfolio has characteristics for potential out-performance in both up and down markets.

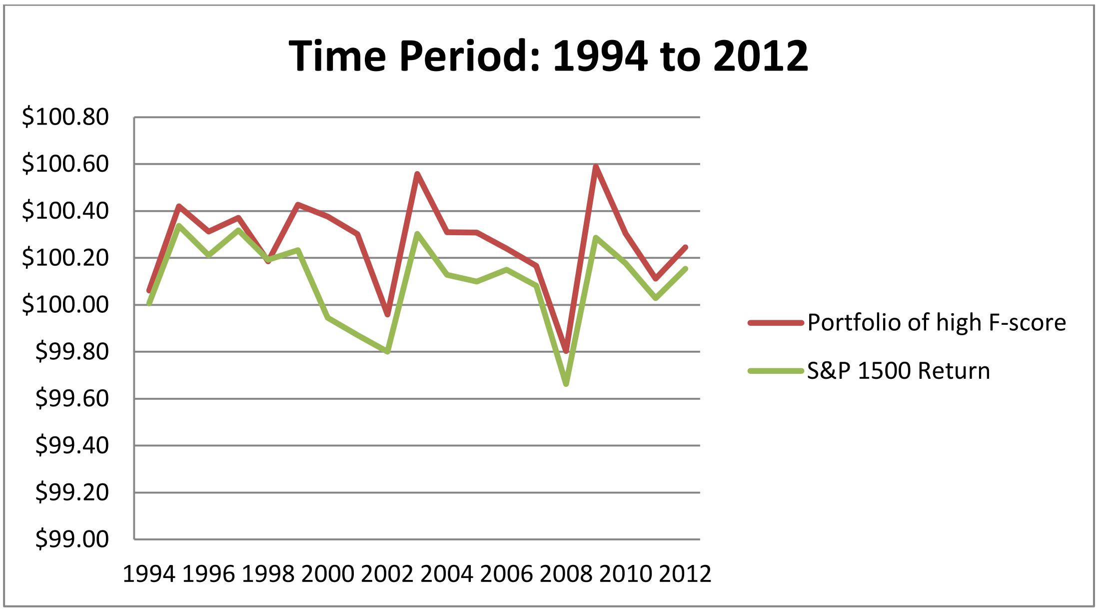

Figure 2.4-9 Investment Performance

The graph in Figure 2.4-9 shows the investment performance of investing in a high F-score (F-score greater than or equal to 7). We take $100 as a basis to get a better idea of the performance. The performance data highlighted in Figure 2.4-9 indicates that a portfolio of high F-scores (greater than or equal to 7) significantly outperforms the S&P 1500 over the review period. The high F-score portfolio experienced a cumulative return of 18% while the S&P 1500 experienced a 15% return over the period. The portfolio twice declined below $100 whilst the benchmark declined four times, emphasizing previous comments about the robustness of the model to limit risk when the market drops significantly.

Chapter three – Statistics

3.1 Financial characteristics

One the primary work of this chapter is to provide descriptive statistics about the financial characteristics of the firms based on using the F-score. Here we expect firms with the highest F-score to have the best subsequent return performance given the strength and the consistency in the fundamental signals. In fact, different tests are formed to see whether the high F-score portfolio outperform the low F-score portfolio. Results are compared using market adjusted returns. Results are tested using both tradition t-statistics as well as implementing a bootstrapping approach to test for differences in portfolio returns. All the results can be found at the end of the chapter in the annexe. Using dummy variables in our panel data analysis we are interested at a cross sectional point of view. In fact we intend to understand which component is more efficient, more effective, and more proactive and on the other side with respect to the time we are interested in knowing which particular year is more efficient, more stable one. By including different variables in our regression we are able to report that the F-score remain significant.

Table 3.1-1 Financial characteristics

Variable	Obs	Mean	Median	Std. Dev.	Min	Max
ME[45]	15940	5732.164	727.1765	21798.41	0	504239.6
TotalA[46]	15936	7936.102	1728.418	28979.04	21	797769
BM[47]	15940	0.3755611	0.2978223	0.7702286	-60.59971	8.503401
ROA[48]	15940	0.0412894	0.0498574	0.1335711	-5.879727	0.7830853
ΔROA[49]	15940	-0.0013463	0.001033	0.1395461	-5.879727	4.94685
ΔMARGIN[50]	15940	0.0421825	0.0007067	2.184291	-30.10921	231.8289
CFOA[51]	15940	0.1059095	0.1008921	0.087311	-1.171011	0.8677104
ΔLIQUID[52]	15940	0.145588	0.0160509	1.507141	-27.65481	53.80119
ΔLEVER[53]	15940	0.0230384	0	0.1866511	-1.197168	2.789499
ΔTURN[54]	15940	0.2470787	0.0040003	21.24361	-472.2617	2601.254
Accruals[55]	15940	-0.0646201	-0.0508745	0.116315	-5.640199	0.7163669

[45] ME: the market value of equity (market value is calculated as the number of shares outstanding at fiscal year-end times closing share price).

[46] TotalA: the total assets at the end of the fiscal year t.

[47] BM: book value of equity at the end of fiscal year t, scaled by ME.

[48] ROA: net income before extraordinary items for the fiscal year preceding portfolio formation scaled by total assets at the beginning of year t.

[49] ΔROA: change in annual ROA for the year preceding portfolio formation. ΔROA is calculated as ROA for year t less the firm's ROA for year t-1.

[50] ΔMargin: gross margin (net sales less cost of goods sold) for the year preceding portfolio formation scaled by net sales for the year, less the firm's gross margin (scaled by net sales) from year t-1.

[51] CFOA: cash flow from operations scaled by total assets at the beginning of year t.

[52] ΔLiquid: change in the firm's current ratio between the end of year t and year t-1. Current ratio is defined as total current assets divided by total current liabilities.

[53] ΔLever: change in the firm's debt-to-assets ratio between the end of year t and year t -1. The debt to asset ratio is defined as the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets.

[54] ΔTurn: change in the firm's asset turnover ratio between the end of year t and year t-1. The asset turnover ratio is defined as net sales scaled by average.

[55] Accruals: net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets.

Table 3.1-1 provides descriptive statistics about financial characteristics of the portfolio of firms; for instance, the mean, the standard deviation, the minimum and the maximum values are presented. As shown, we see that we have 15,940 observations; the mean of market value is $5,732.164 million and the standard deviation is $21,798.41 million. The minimum is 0, and the maximum is $504,239.6 million. There are only 15,936 observations on total assets, so some of the observations are missing. Firms have a mean (median) BM ratio of 0.3755 (0.2978223) as shown in the table; the average (median) ROA realization is 0.0412 (0.0498) and the average and median firms show a decline in ΔROA for the average -0.0013 and median of 0.0010. Also, the table shows an increase in liquidity with an average (median) of 0.1455 (0.0160) and an increase in leverage of 0.0230 (0) average and median respectively. An increase in turnover can also be highlighted: the average (median) is 0.2470 (0.0040).

3.2 Buy-and-hold returns from a high Piotroski F-score investment between 2000 to 2012

Table 3.2-1 Summary statistics

Stats	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile
Raw[56]	0.1285448	-0.3792156	-0.148099	0.0863173	0.3228463	0.6350249
Market-Adj[57]	0.0817551	-0.355995	-0.1760604	0.0217744	0.2489982	0.5392746

Table 3.2-1 presents one-year buy and hold returns for a portfolio of high Piotroski F-scores (7 to 9) along with the percentage of firms in the portfolio with positive raw and market-adjusted returns over the respective investment horizon. The high Piotroski portfolios earn positive market-adjusted returns in the one year following portfolio formation. The average (median) of the market-adjusted return is 0.0817 (0.021) respectively. This reflects the ability for

[56] A raw return is calculated as a 12-month buy and hold of the firm. Return compounding ends the earlier of one year after return compounding starts or the last day of reported trading. IF the firm is delisted, the delisting return is assumed to be zero.

[57] The market-adjusted return equals the firm's 12-month buy and hold return less the buy and hold return on the value-weighted market index over the same investment horizon.

the high F-score portfolio to capture better subsequent returns, as it can be seen the 90th percentile of the portfolio earns an approximately 53% market-adjusted return whereas the 10th percentile of the portfolio earn an approximately -35% market-adjusted return.

3.3 Correlation analysis between one-year stock return and market-adjusted return: the nine fundamental signals for a high score Piotroski portfolio above 7

Table 3.3-1 Correlation matrix

	SR12M	MARET	ROA	VROA	VMARGIN	CFOA	VLIQUID	VLEVER	VTURN	Accruals	EQOFFER	Fscore
SR12M	1.000											
MARET	0.931	1.000										
ROA	0.028	0.038	1.000									
VROA	0.158	0.136	0.133	1.000								
VMARGIN	0.028	0.022	-0.055	0.201	1.000							
CFOA	0.094	0.111	0.728	0.067	0.026	1.000						
VLIQUID	0.059	0.066	0.017	0.054	0.093	-0.012	1.000					
VLEVER	-0.095	-0.089	-0.104	-0.219	-0.062	-0.121	0.076	1.000				
VTURN	0.017	0.007	-0.143	-0.061	0.249	-0.148	0.395	0.143	1.000			
Accruals	-0.102	-0.115	0.118	0.058	-0.103	-0.594	0.038	0.053	0.046	1.000		
EQOFFER	0.000	-0.005	-0.135	-0.113	-0.006	0.154	-0.026	-0.016	-0.027	-0.382	1.000	
Fscore	0.058	0.064	-0.014	0.020	0.064	-0.041	0.107	0.099	0.106	0.042	0.063	1.000

Table 3.3-1 presents a correlation analysis between one-year stock return, the market-adjusted return and the nine fundamental signals attached to the construction of the F-score for a high Piotroski portfolio (7 to 9). As expected, F-score has a significant correlation with one-year stock return and market-adjusted return – 0.058 and 0.064 respectively. The two strongest explanatory variables are the ΔROA and CFOA; in line with the findings provided by Piotroski (2000), these variables have a correlation of 0.136 and 0.111 respectively with one-year market-adjusted returns. The sample represents 2489 observations between 2000 and 2012.

3.4 Table 4: One-year market-adjusted returns since 2000 by F-score

Table 3.4-1 Summary statistics for one-year market-adjusted return

Fscore	mean	p10	p25	p50	p75	p90	N
0	-0.290	-0.700	-0.557	-0.389	-0.089	0.272	79
1	-0.200	-0.639	-0.507	-0.298	-0.020	0.404	165
2	-0.010	-0.535	-0.354	-0.123	0.153	0.595	622
3	0.030	-0.442	-0.270	-0.045	0.220	0.578	1932
4	0.014	-0.395	-0.222	-0.029	0.179	0.442	2778
5	0.070	-0.320	-0.160	0.017	0.222	0.484	4185
6	0.127	-0.279	-0.114	0.067	0.277	0.565	3690
7	0.184	-0.218	-0.072	0.112	0.336	0.621	1900
8	0.256	-0.210	-0.052	0.149	0.413	0.825	550
9	0.301	-0.318	-0.141	0.082	0.522	1.482	39
High P (7-9)	0.201	-0.219	-0.069	0.119	0.353	0.672	2489
Low P (0-3)	-0.001	-0.501	-.315	-0.082	0.186	0.566	2798
Total	0.081	-0.356	-0.176	0.021	0.248	0.539	15940
Bootstrap (p-Value)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
High – Low Bootstrap (p-value)		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

Table 3.4-1 shows the mean, the median, the 10th, 25th, 75th and 90th percentile for one-year market-adjusted performance by F-score. For example, stocks scoring a maximum F-score of 9 have an average (median) of 30.1% (8.2%) respectively; the 75th percentile stock delivered a return of 52.2% whilst the 25th percentile stock delivered a return of -14.1%. Most of the observations are clustered around F-scores between 3 and 7, meaning that a vast majority of the firms have conflicting performance signals. In contrast, 2489 firms are classified as high F-scores (scores of 7 to 9) and 2798 firms are classified as low F-scores (scores of 0 to 3). As can be noticed, high F-score firms significantly outperform low F-score firms as described: mean (median) market-adjusted returns of 20.1% (11.9%) versus -0.1% (-8.2%). Also, it can be noticed that the 10th percentile, 25th percentile, 75th percentile and 90th percentile returns of high F-score

are significantly higher than the corresponding returns of the low F-score. The model confirms our view that it is good at identifying potential winners from losers. It can be noticed that there is an overall steady improvement in performance in line with a rise in the F-score. For instance, there is a 24% difference between the 25^{th} percentile performances in the low F-score versus the high F-score. Please find bootstrapping results in Appendix A.

3.4.1 Bar charts of F-score by mean market-adjusted return

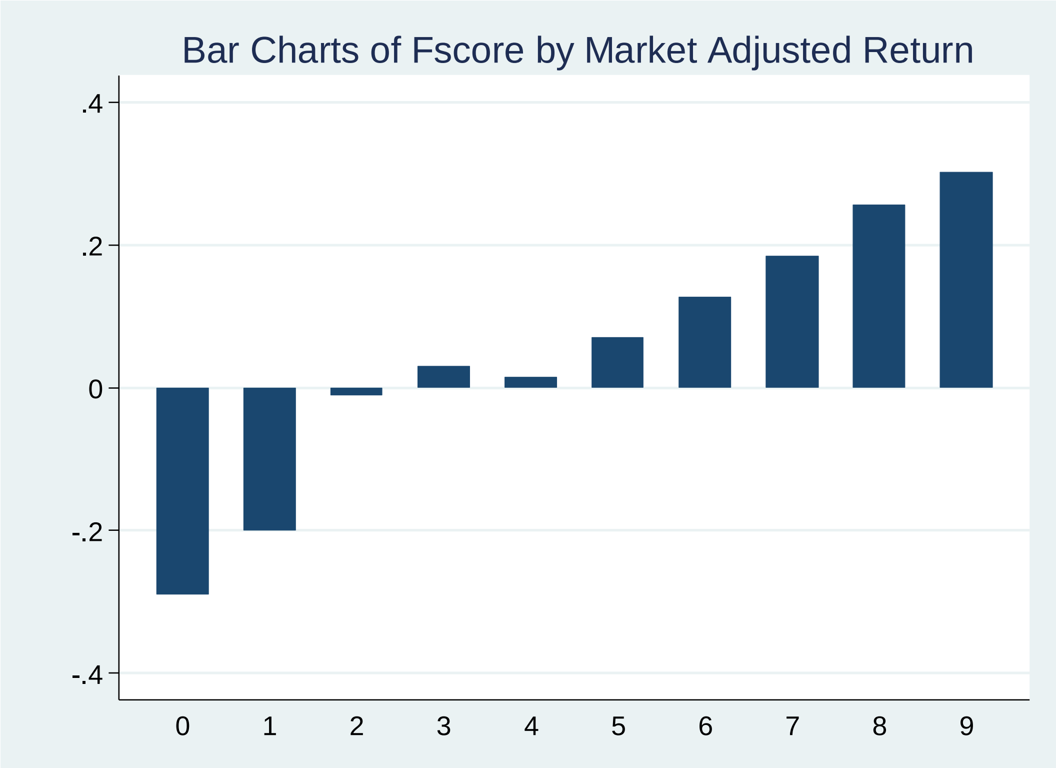

Figure 3.4-1 Bar chart displays F-score by market-adjusted return

This bar chart in Figure 3.4-1 describes the average market-adjusted return of buying the different F-scores. An investor would expect to see that steady growth in the returns, suggesting that the model is well adjusted and is distinguishing winners from losers. As can be noticed, the highest adjusted mean market return is earned when forming a portfolio of an F-score of 7 to 9 and a negative return can be used in a short strategy to benefit from a portfolio of 0 to 3.

The difference between the 0 and 9 F-score over the one-year market-adjusted return is about 60%.

3.4.2 Histogram description: histogram of market-adjusted return, log market equity and log book to market are displayed below

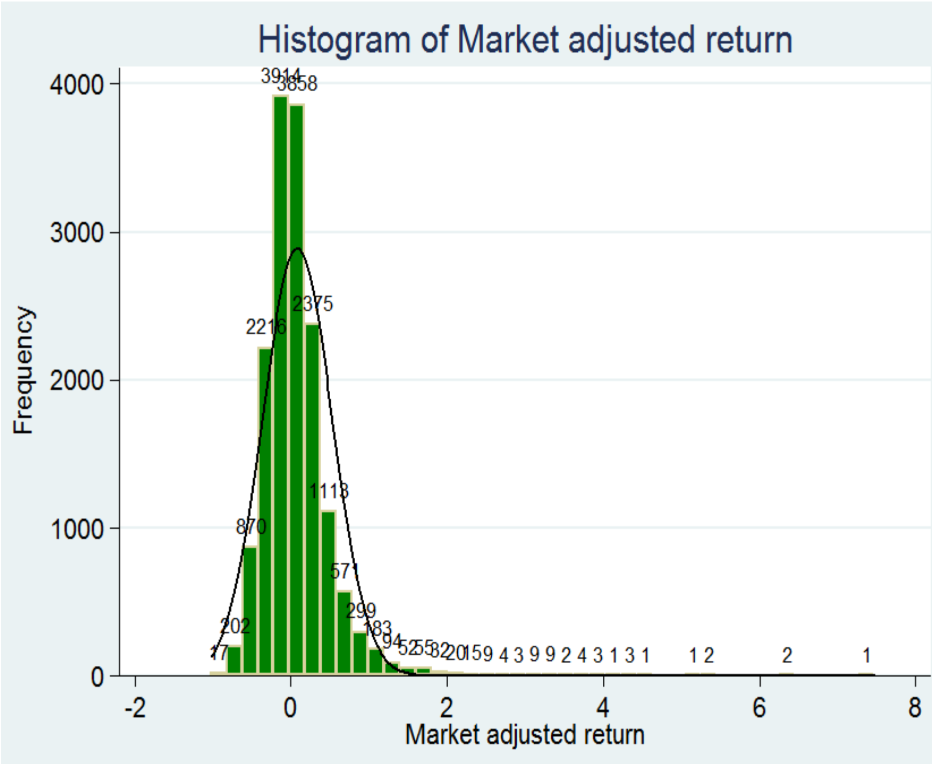

Figure 3.4-2 Histogram of market-adjusted return

Here in Figure 3.4-2, we check for the distribution of our dependent variables, so that we know its properties for when we want to conduct some regression analysis. From the histogram we can see that our dependent variable is reasonably normally distributed. The same analysis has been applied to two independent variables, the log market equity and the log book to market, which we present below. From the two histograms in figures 3.4-3 and 3.4-4 we can see that our independent variables are both reasonably normally distributed; especially, it is remarkable to see how the log market equity displays such tidy distribution characteristics.

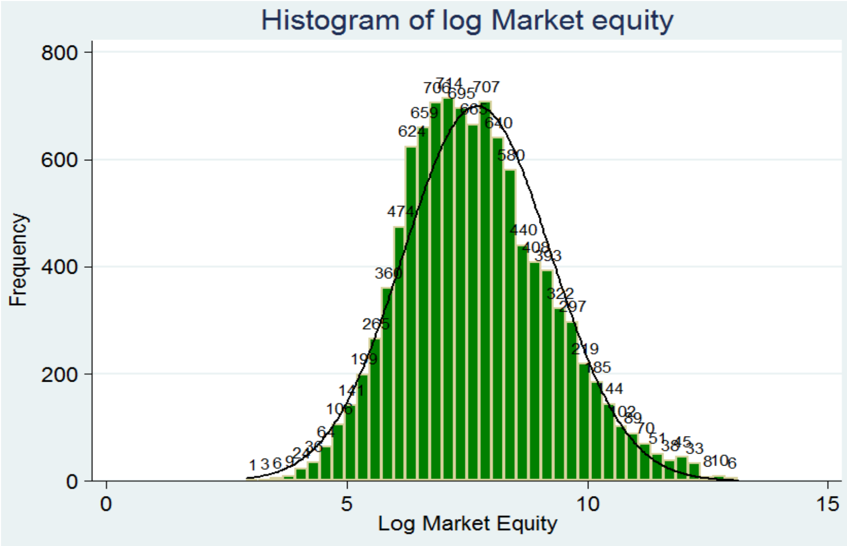

Figure 3.4-3 Histogram of log market equity

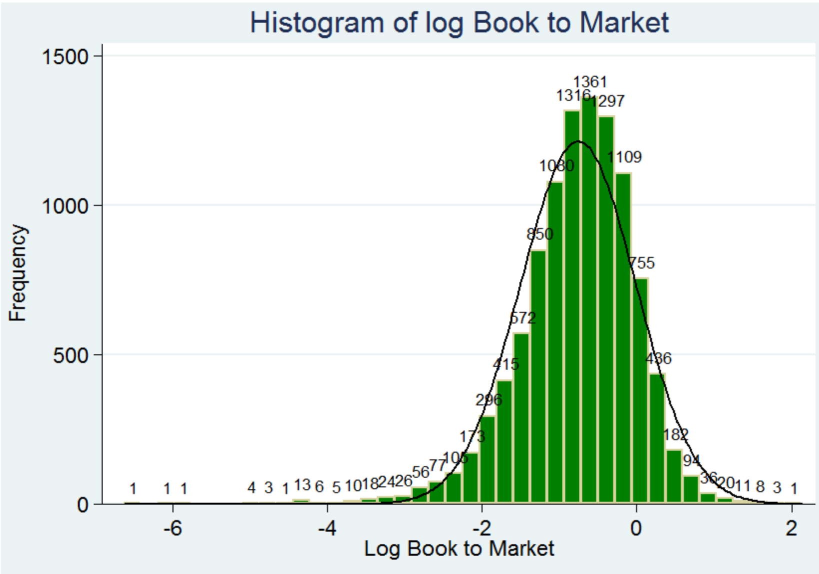

Figure 3.4-4 Histogram of log book to market

3.5 One-year market-adjusted[58] buy and hold returns based on using the F-score by size partition[59]

Table 3.5-1 Displays the F-score by size of the firms

Fscore	High firms			Medium firms			Low firms		
	mean	median	N	mean	median	N	mean	median	N
0	-0.2887431	-0.3536437	39	-0.2373254	-0.3733679	19	-0.3416842	-0.434902	21
1	-0.1729989	-0.3113576	89	-0.1146113	-0.187818	32	-0.3178241	-0.3419259	44
2	0.068076	-0.0728179	341	-0.042889	-0.1235814	129	-0.1601509	-0.2001317	152
3	0.0822197	-0.0130017	941	0.0351946	-0.0162737	588	-0.0971428	-0.1556682	403
4	0.0349367	-0.0176967	1330	0.0263272	-0.0142387	874	-0.049297	-0.081667	574
5	0.0924084	0.0312326	2065	0.0909248	0.032135	1277	-0.0160766	-0.0505634	843
6	0.1481785	0.0784987	1908	0.1438068	0.0903078	1119	0.0392119	-0.0104748	663
7	0.2275711	0.135344	1000	0.1725629	0.1215329	571	0.0725483	0.0314488	329
8	0.3192376	0.2193965	277	0.2753888	0.1520601	153	0.0867398	0.0520699	120
9	0.7009261	0.4379594	18	0.0228867	-0.012721	12	-0.1245719	-0.0867512	9
High P	0.253758	0.1564943	1295	0.191498	0.1224708	768	0.0723931	0.0277475	458
Low P	0.0524289	-0.0445295	1410	0.009095	-0.048336	736	-0.136534	-0.1865906	620

Table 3.5-1 shows the market returns of our sample by distinguishing firms in low, medium and high book to market.

The highest market-adjusted return is earned in the high book to market firms, emphasizing Piotroski's (2000) idea that the F-score ability is more reliable on the high book to market firms. Our analysis emphasizes this point and highlights that when using the F-score strategy the strongest benefit from analyzing financial statement is concentrated on the high book to market firms, i.e., value firms. Return difference between the high F-score portfolio (7 to 9) and a low F-score portfolio (0 to 3) in the high book to market sample is 20.13%. However, the shift in the mean and median returns is still significant in the medium portfolio.

The question is whether the strategy earned subsequent returns across all categories. The book to market is defined as the book value of equity at the end of fiscal year t, scaled by market capitalization (ME).

[58] The market-adjusted return equals the firm's 12-month buy and hold return less the buy and hold return on the value-weighted market index over the same investment horizon.
[59] The 30 and 70 percentile cutoffs from the prior year's distribution of firm book to market are used to classify the sample into high, medium and low firms each year.

3.5.1 Bar chart F-score and book to market against market-adjusted return

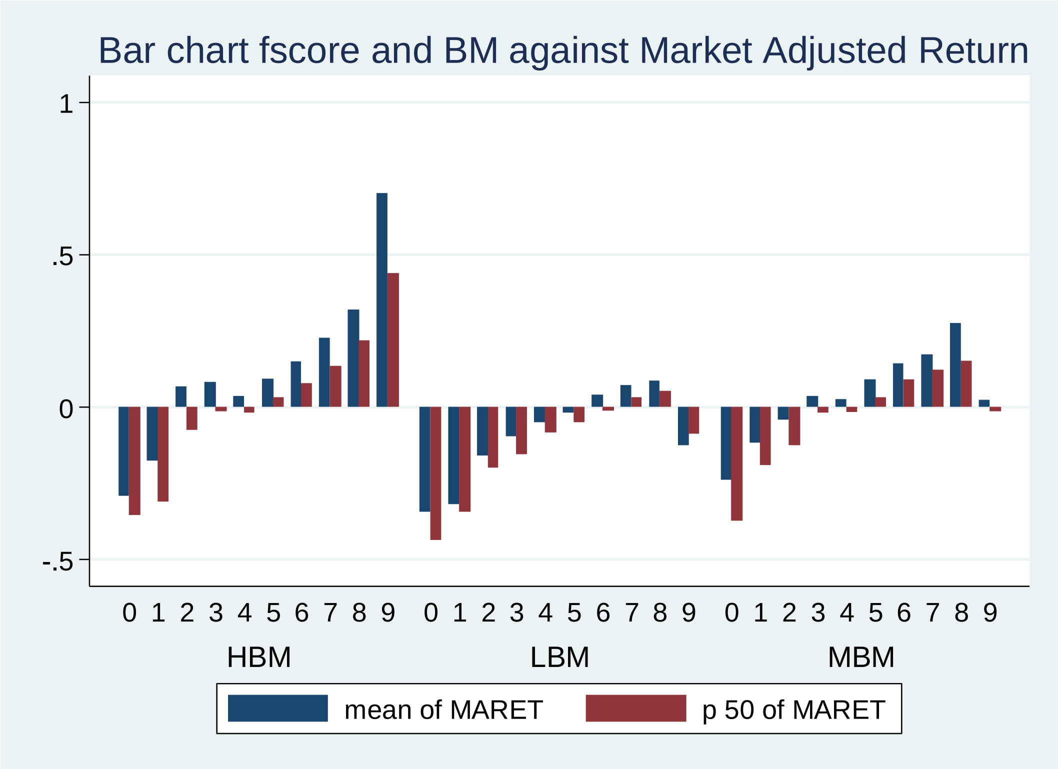

Figure 3.5-1 Displays a bar chart of the F-score by book to market and market-adjusted return

This chart in Figure 3.5-1 emphasizes our previous point of view that the F-score strategy is more efficient in the high book to market firms rather than in the low ones, reflecting that an investor can earn high returns by focusing on the high book to market segment of the sample.

This charts shows that returns based on book to market tend to have more positive returns in high book to market firms rather than in the low book to market ones. This explanation is consistent with a reversal effect and to some extent with small firms because high book to market firms tend to be small.

3.6 Analysis of variance

Table 3.6-1 Summary of the variance

	Number of obs =	15940	R-squared =	0.0343	
	Root MSE =	.437996	Adj R-squared =	0.0337	

Source	Partial SS	df	MS	F	Prob > F
Model	108.545341	10	10.8545341	56.58	0.0000
BM	14.8352055	1	14.8352055	77.33	0.0000
Fscore	92.3922728	9	10.2658081	53.51	0.0000
Residual	3055.83097	15929	.191840729		
Total	3164.37631	15939	.198530417		

Table 3.6-1 shows the analysis of variance (ANOVA) for the market-adjusted return. The sum of squares (SS) of the regression (108.482) is the portion of the variance of the dependent variable (MARET) that is explained by the independent variable (the BM and Fscore). The MS for the residual (0.1918) shows the variance of the unexplained portion of MARET (market-adjusted return), that is the portion of return that is independent of the F-score and the book to market.

3.6.1 Box plot of market-adjusted return by F-score

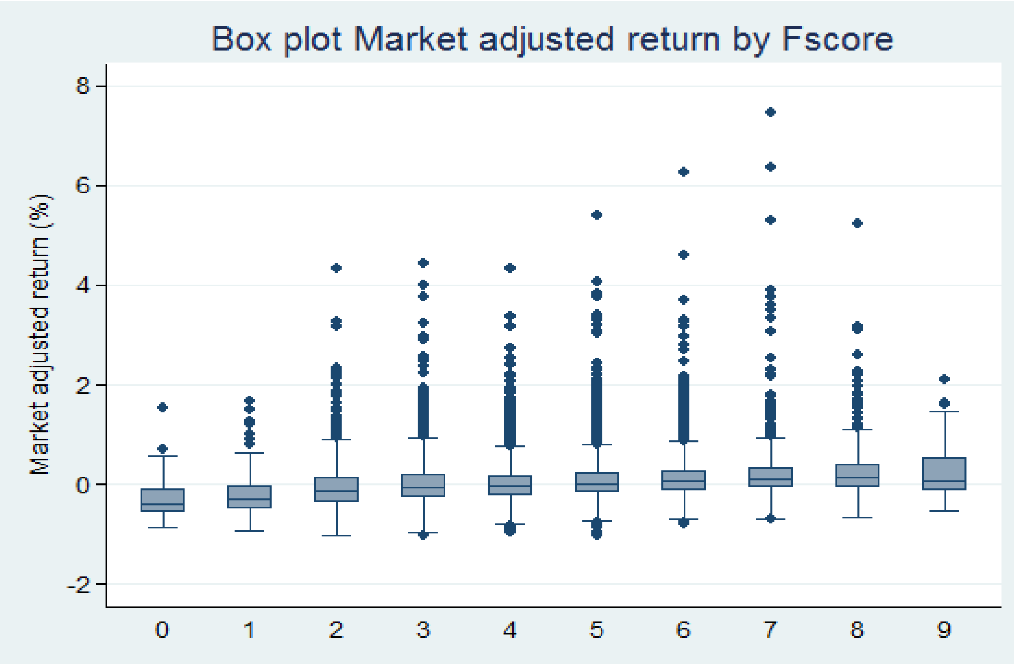

Figure 3.6-1 Displays a box plot by market-adjusted return and F-score

Here we use a graph box in Figure 3.6-1; the main ingredient of a box plot is the eponymous box, used to indicate the lower and upper quartiles of the variables or group being plotted against a magnitude scale. The median is represented by a line subdividing the box. The length of the box represents the interquartile range. The lines extending vertically from the boxes indicate variability outside the upper and lower quartiles, emphasizing that subsequent returns can be earned when an investor is focusing on buying stocks rated with an F-score of 7. This helps to indicate the degree of dispersion and skewness in the data and could help to identify outliers.

3.6.2 Box plot of market-adjusted return by F-score and size

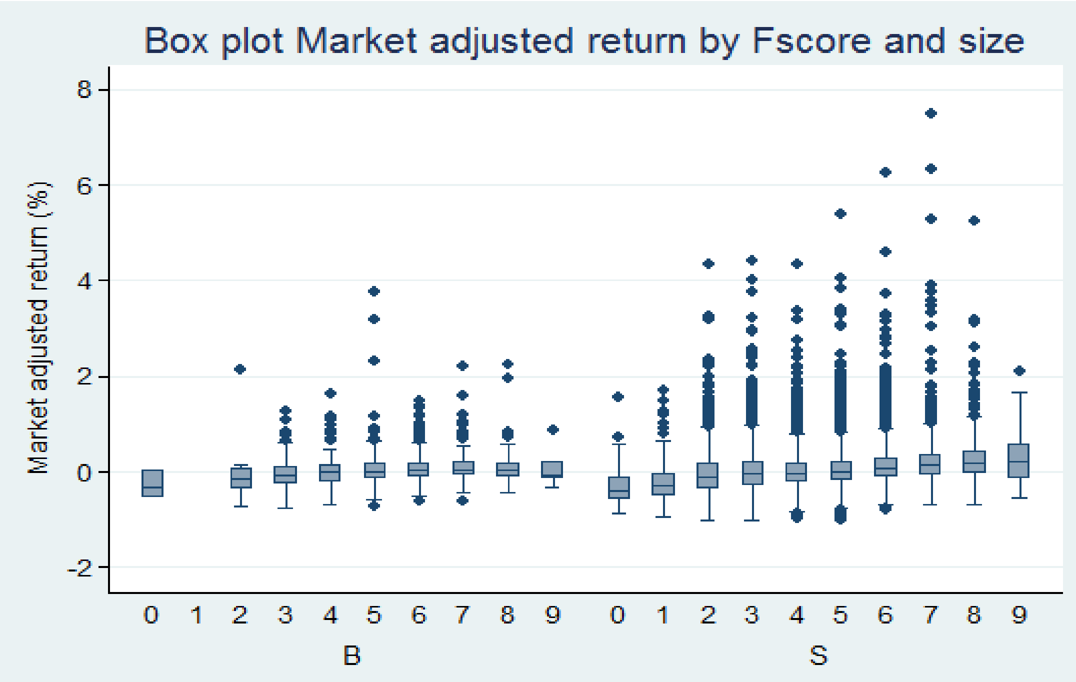

Figure 3.6-2 Displays a box plot by market-adjusted return and by size

This graph in Figure 3.6-2 describes a box plot of the market-adjusted return by F-score and size; the idea is to show that the F-score is more significant in small stocks than in big stocks, as highlighted by the magnitude of the different boxes.

3.6.3 Box plot of market-adjusted return by F-score and book to market

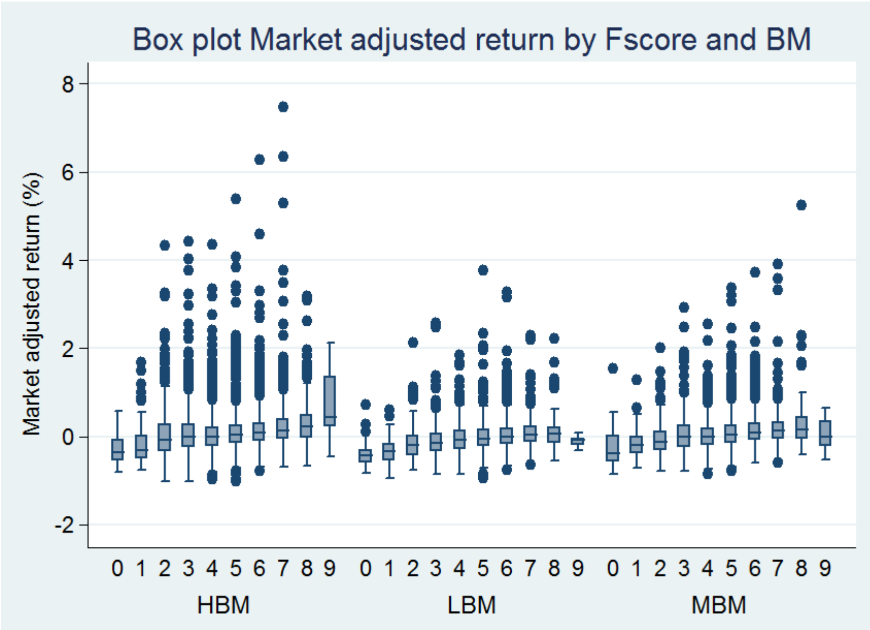

Figure 3.6-3 Displays a box plot by book to market and market-adjusted return

The graph in Figure 3.6-3 above uses a box plot; the main reason is to indicate that the strategy is more significant among high book to market firms instead of low book to market firms, showing that the F-score strategy is more profitable to an investor willing to invest in value stocks. The whiskers are the two vertical lines below and above the box which are terminated by small horizontal lines called the fences. The upper fence is the highest value of the distribution that is smaller than or equal to the third quartile plus 1.5 times the interquartile range. The lower fence is the lowest value of the distribution that is greater than or equal to the first quartile minus 1.5 times the interquartile range.

Observations below the lower fence or above the upper fence are regarded as outliers and are plotted with single plot symbols.

3.6.4 Scatter diagram of market-adjusted return and book to market

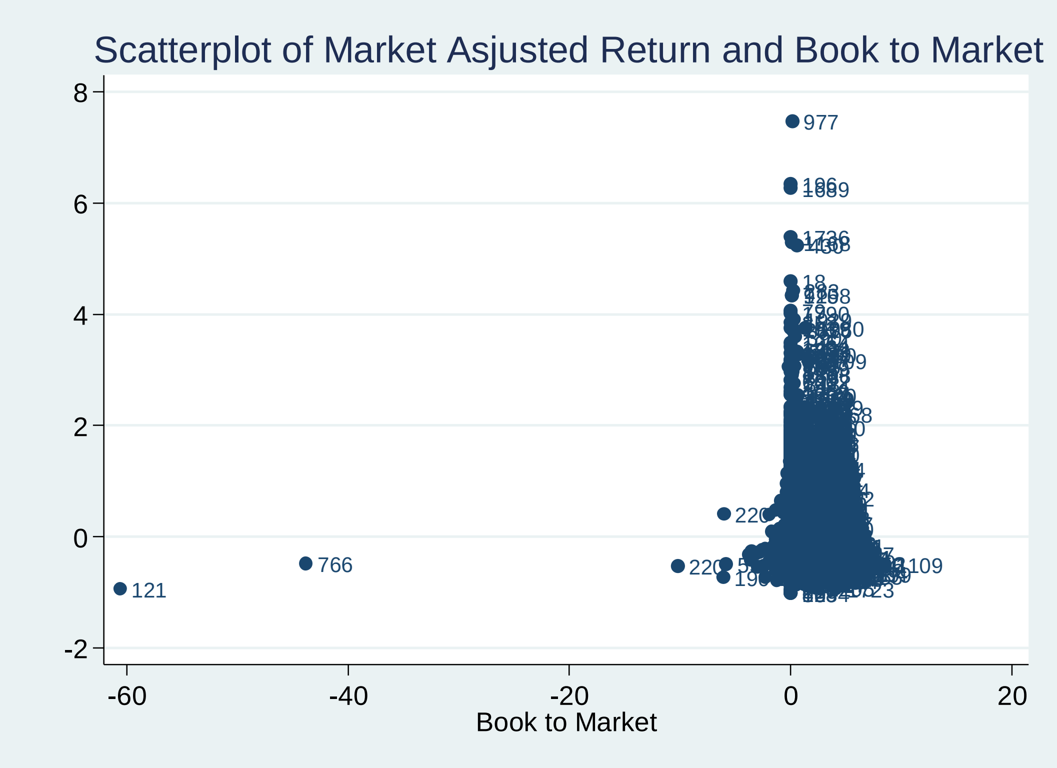

Figure 3.6-4 Displays a scatter plot by book to market and market-adjusted return

This scatter diagram in Figure 3.6-4 is intended to analyze the relationship between the market-adjusted return and book to market. The market-adjusted variable is plotted on the vertical axis and the book to market is plotted on the horizontal axis. There is a weak positive correlation as the value of y increases slightly as the value of x increases. It appears that, as the variables on the horizontal axis change, the variables on the vertical axis seem to vary within a relatively small range, with the tendency to increase. This graph helps as well to outline outliers which tend to be far away from the sample.

3.6.5 Histogram to describe the market-adjusted return by sector and F-score

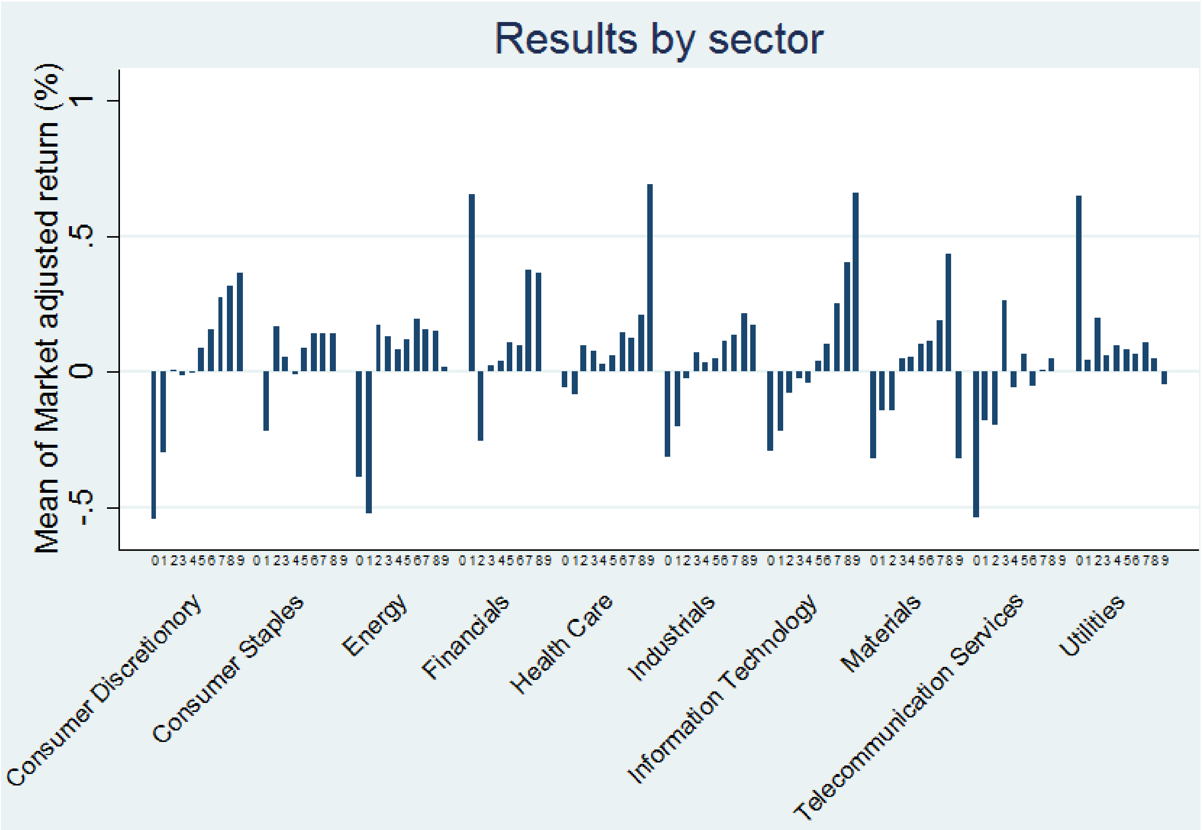

Figure 3.6-5 Displays the F-score by sector and market-adjusted return

This graph in Figure 3.6-5 shows in the form of a histogram the distributions that vary according to the sector exposure and to the F-score. The information technology sector seems to capture the F-score negative market-adjusted return for a low F-score (0 to 4) with a gradual increase in the return; the same can be noticed when looking at high F-scores (5 to 9). The consumer discretionary sector also seems to capture the F-score in a similar manner.

When someone is willing to invest in our strategy s/he will have more chance to earn subsequent returns on the health care sector if s/he wants to buy a stock rated out of 9. The same notion can be applied in the information technology sector as well as in the materials and consumer discretionary sectors.

When an investor is willing to benefit from a low F-score portfolio such as selling stocks rated out with a 0, s/he should focus on the consumer discretionary, the energy and the telecommunication services.

A useful way to define industry groups is given by the North American Industry Classification System or NAICS codes[60].

3.6.6 Results by sector relative to a high F-score or a low F-score portfolio

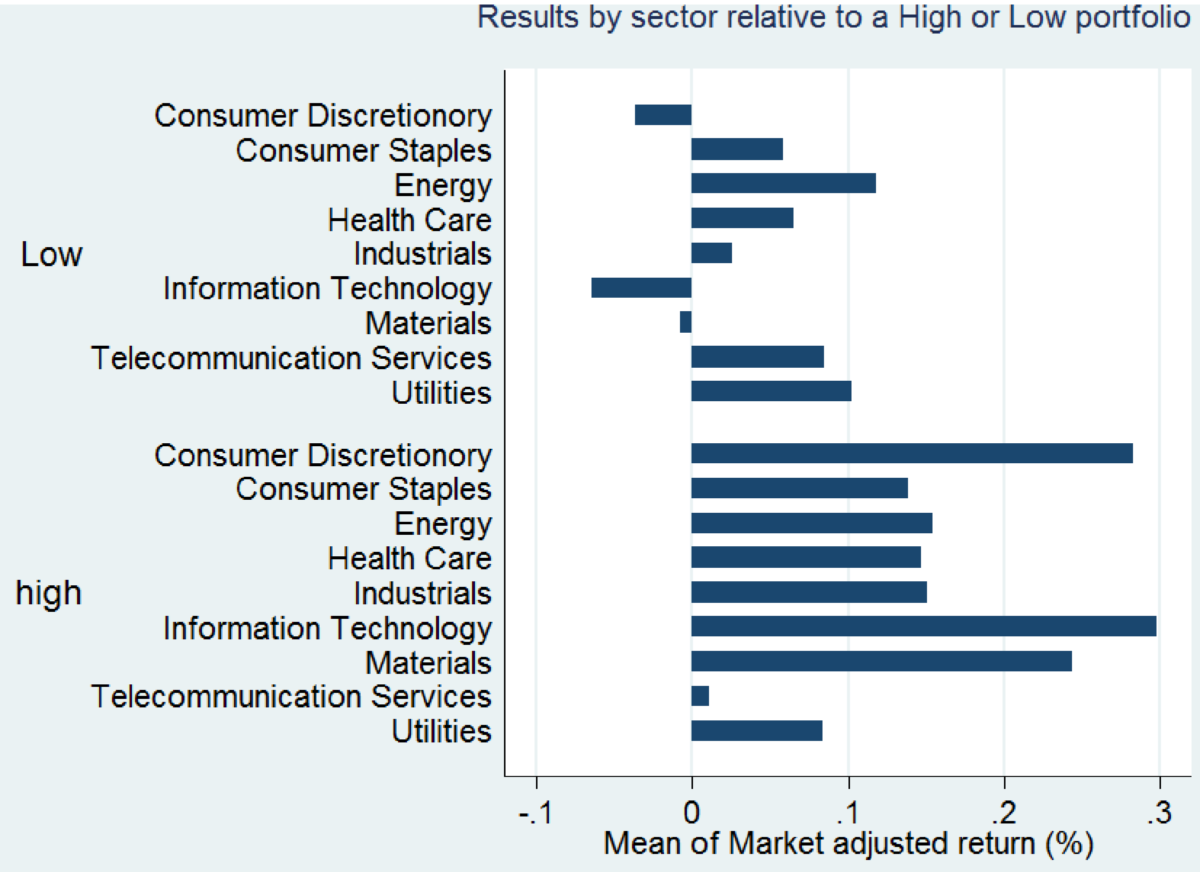

Figure 3.6-6 Displays the F-score by sector and low or high portfolio

The two charts above in Figure 3.6-6 highlight the different sector exposure for the high F-score (7 to 9) and the low F-score (0 to 3) portfolio from 2000 to 2012. It suggests that an investor can benefit from higher returns by increasing the weights where the portfolio is performing better. Therefore, we would recommend investors to invest in information technology, materials and consumer discretionary when looking at the high F-score portfolio; the same sectors can be applied within the low F-score if the investor is willing to short stocks. In other words, the sector distributions are relatively similar in the sense that the F-scores for the low and high F-score portfolio capture the consumer discretionary, information technology and materials sectors. For instance, the consumer discretionary sector accounts for 27% of the high F-

[60] These codes are used for firms operating inside the NAFTA (North American Free Trade Agreement) region which includes the US, Mexico and Canada. NAICS codes replaced the Standard Industry Classification or SIC codes previously used in the US.

score and -5% of the low F-score portfolio. Information technology accounts for 29% of the high F-score portfolio and -9% of the low F-score and, finally, materials account for 24% of the high F-score portfolio and -2% of the low F-score portfolio. It can be seen as well that, in the sector distribution of our two portfolios, we intentionally removed the financials sectors as the strategy is not appropriate to understand financial statements from the firms' part of the financial sectors due to different complexity.

3.7 Descriptive statistics for the high and low F-score portfolios and the complete sample

Table 3.7-1 Displays statistics for the low and high portfolio

	All Firms	High F-score	Low F-score	Difference High - Low
ME[61]				
Mean	5732.164	7771.266	2335.693	5435.573
Median	727.1765	1108.555	417.1557	691.3943
BM ratio[62]				
Mean	0.3755611	0.3576918	0.3637779	-0.00609
Median	0.2978223	0.2809939	0.2844	-0.00341
ΔLeverage[63]				
Mean	0.0230384	0.0471115	0.0848551	-0.03774
Median	0	0.0140261	0	0.014026
Accruals[64]				
Mean	-0.0646201	-0.0547397	-0.0891148	0.034375
Median	-0.0508745	-0.0482923	-0.056751	0.008459

[61] ME: the market value of equity (market value is calculated as the number of shares outstanding at fiscal year-end times closing share price).

[62] BM: book value of equity at the end of fiscal year t, scaled by ME. Stocks are allocated to two size groups (small or big) based on whether that particular stock's market equity is below or above the median ME for the NYSE stocks in the stock universe. Stocks also are allocated independently to three BE/ME groups (low, medium and high). The break points are the bottom 30%, middle 40%, and the top 30% BE/ME values of the NYSE stocks in the stock universe

[63] ΔLever: change in the firm's debt-to-assets ratio between the end of year t and year t -1. The debt to asset ratio is defined as the firm's total long-term debt (including the portion of long-term debt classified as current) scaled by average total assets.

[64] Accruals: net income before extraordinary items less cash flow from operations, scaled by beginning of the year total assets.

This table, 3.7-1, shows the differences in the mean and median realization between the high and low F-score portfolio. The difference in the average (median) in the market equity value is 5935.573 (691.3943) respectively; the difference in the book to market ratio for the average (median) is -0.00609 (-0.00341). Also, using the same method of description, the difference in the average (median) in the change in leverage is -0.03774 (0.014026). Finally, the difference in the accruals components for the average (median) is 0.034375 (0.008459).

Following Piotroski(2000) work it conveys here to present the results using a panel data analysis.

3.8 Panel data analysis

Table 3.8-1 Panel data regression – linear regression 1

Linear regression:

Source	SS	df	MS
Model	156.960256	3	52.3200854
Residual	1797.44086	10362	.173464665
Total	1954.40112	10365	.188557754

Number of obs =	10366
F(3, 10362) =	301.62
Prob > F =	0.0000
R-squared =	0.0803
Adj R-squared =	0.0800
Root MSE =	.41649

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	-.0051063	.0028971	-1.76	0.078	-.0107851	.0005726
logBM	-.1441232	.0057716	-24.97	0.000	-.1554366	-.1328098
Fscore	.0387054	.0027794	13.93	0.000	.0332573	.0441535
_cons	-.1812343	.0227472	-7.97	0.000	-.2258232	-.1366455

Model 1: $MARET_i = \alpha + \beta_0 \log(ME_i) + \beta_1 \log(BM_i) + \beta_3 Fscore + \varepsilon_i$

The pooled model fits the data at the 0.05 significance level (F=301.62, p<0.000). R^2 of 0.0803 says that this model accounts for 8% of the total variance. The model has the intercept of -0.1812343 and slope of -0.1441 for logBM and -0.005106 for logME. The coefficient on F-score indicates that after controlling for size and book to market a one-point improvement in the aggregate score is associated with a 3.8% increase in the one-year market-adjusted return. Notice that the logME is only significant at the 10% level.

Table 3.8-2 Panel data regression – linear regression 2

Source	SS	df	MS
Model	163.157547	5	32.6315093
Residual	1791.24357	10360	.172899958
Total	1954.40112	10365	.188557754

Number of obs	= 10366
F(5, 10360)	= 188.73
Prob > F	= 0.0000
R-squared	= 0.0835
Adj R-squared	= 0.0830
Root MSE	= .41581

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	-.0068629	.0029311	-2.34	0.019	-.0126085	-.0011173
logBM	-.1445041	.0057834	-24.99	0.000	-.1558407	-.1331674
Fscore	.0376738	.0029673	12.70	0.000	.0318574	.0434902
Accruals	.2217996	.0397057	5.59	0.000	.1439688	.2996304
EQOFFER	-.0032087	.0132889	-0.24	0.809	-.0292574	.0228401
_cons	-.1458152	.0236374	-6.17	0.000	-.1921491	-.0994813

Model 2: $MARET_i = \alpha + \beta_0 \log(ME_i) + \beta_1 \log(BM_i) + \beta_3 Fscore + \beta_4 Accruals + \beta_5 EQOFFER + \varepsilon_{it}$

The addition of variables designed to capture accrual reversal, and a prior equity issuance has no impact on the robustness of the F-score to predict future returns. The pooled model fits the data at the 0.05 significance level (F=188.73, p<0.000). R^2 of 0.0835 says that this models accounts for 8% of the total variance. Also, the coefficient on F-score is indicating that, after controlling for size and book to market, accruals and equity offering a one-point improvement in the aggregate score are associated with a 3.8% increase in the one-year market-adjusted return. Notice that the EQOFFER (issues of new shares) is not significant.

Panel Data analysis:

Fixed-effects:

Panel data, also called longitudinal data or cross-sectional time series data, are data where the same entities' (panels) firms were observed at multiple points in time. We first apply a fixed-effect regression to control for omitted variables that differ among panels but are constant over time. We assume that there are other effects that are different among firms but constant over time.

Model 3: $MARET_{it} = \alpha + \beta_0 \log(ME_{it}) + \beta_1 \log(BM_{it}) + \beta_3 Fscore_{it} + \varepsilon_{it}$

Table 3.8-3 Fixed-effects regression

Fixed-effects (within) regression				Number of obs	=	10366
Group variable: Idd				Number of groups	=	1375
R-sq: within = 0.1577				Obs per group: min	=	1
between = 0.0559				avg	=	7.5
overall = 0.0718				max	=	13
				F(3,8988)	=	560.89
corr(u_i, Xb) = -0.6471				Prob > F	=	0.0000

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	.0013952	.0094242	0.15	0.882	-.0170785	.0198688
logBM	-.3673396	.0105298	-34.89	0.000	-.3879805	-.3466987
Fscore	.0287256	.0029524	9.73	0.000	.0229382	.034513
_cons	-.350465	.0688812	-5.09	0.000	-.4854878	-.2154421
sigma_u	.32100037					
sigma_e	.39791356					
rho	.39422542	(fraction of variance due to u_i)				

F test that all u_i=0: F(1374, 8988) = 1.72 Prob > F = 0.0000

The output shows that it is a fixed-effects regression, with a group variable Idd. There are a total of 10,366 observations and 1375 groups (firms). The observations are per group; in this case year ranges from 1 to 13. Plugging the coefficients into the above model we have:

$$MARET_{it} = -0.350 + 0.001 \log(ME_{it}) + -0.367 \log(BM_{it}) + 0.028 Fscore_{it} + \varepsilon_{it}$$

39.4% of the variance is due to the differences across panels as shown by 'Rho'.

The intercept, trend and coefficient on market-adjusted return are allowed to vary with the country.

Time fixed-effects:

In this case we assume that there are unobserved effects that vary across time rather than across firms that can impact the market-adjusted return. For example, macroeconomic events may impact firms in the same sector in the same way but may be different at different points in time. For instance, we run a time fixed-effects regression so that the model looks like:

Model 4: $MARET_{it} = \alpha_t + \beta_0 \log(ME_{it}) + \beta_1 \log(BM_{it}) + \beta_3 Fscore_{it} + \varepsilon_{it}$

So the intercept includes the variation of time rather than panels. In stata, you can run time fixed effect model using “areg” and have “year” as the variable to be observed.

Table 3.8-4 Time fixed-effects regression

Linear regression, absorbing indicators

Number of obs	=	10366
F(3, 10350)	=	326.44
Prob > F	=	0.0000
R-squared	=	0.1220
Adj R-squared	=	0.1207
Root MSE	=	0.4072

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	.0004758	.0028577	0.17	0.868	-.0051259	.0060775
logBM	-.1440538	.0057158	-25.20	0.000	-.1552579	-.1328496
Fscore	.0398687	.002747	14.51	0.000	.0344841	.0452533
_cons	-.2300201	.0224774	-10.23	0.000	-.2740801	-.1859601
fy	F(12, 10350) =		40.929	0.000		(13 categories)

In the time fixed-effects model we are assuming that the slope for market-adjusted return is the same for all years but the intercept is different. Please find regression below for each year. Time effect is needed it as a joint test following Piotroski (2000) to see if the dummies for all years are equal to zero. In the case they are , no fixed effect test is needed.

Table 3.8-5 Statistics regression for each year

Source	SS	df	MS
Model	238.391809	15	15.8927873
Residual	1716.00931	10350	.165798001
Total	1954.40112	10365	.188557754

Number of obs	=	10366
F(15, 10350)	=	95.86
Prob > F	=	0.0000
R-squared	=	0.1220
Adj R-squared	=	0.1207
Root MSE	=	.40718

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	.0004758	.0028577	0.17	0.868	-.0051259	.0060775
logBM	-.1440538	.0057158	-25.20	0.000	-.1552579	-.1328496
Fscore	.0398687	.002747	14.51	0.000	.0344841	.0452533
yr1	-.0077478	.0256307	-0.30	0.762	-.0579889	.0424933
yr2	-.1132175	.025805	-4.39	0.000	-.1638003	-.0626346
yr3	-.2380828	.025903	-9.19	0.000	-.2888578	-.1873078
yr4	-.2099524	.0262622	-7.99	0.000	-.2614313	-.1584735
yr5	-.264945	.0265452	-9.98	0.000	-.3169788	-.2129112
yr6	-.2856704	.0265242	-10.77	0.000	-.337663	-.2336777
yr7	-.3348224	.0269514	-12.42	0.000	-.3876524	-.2819924
yr8	-.3348726	.0267929	-12.50	0.000	-.3873918	-.2823534
yr9	-.2102259	.0257142	-8.18	0.000	-.2606308	-.159821
yr10	-.1627501	.0267883	-6.08	0.000	-.2152603	-.1102399
yr11	-.2369007	.0269368	-8.79	0.000	-.289702	-.1840995
yr12	-.2889866	.0266057	-10.86	0.000	-.3411389	-.2368343
yr13	-.3031204	.0270036	-11.23	0.000	-.3560526	-.2501882

Random-effects regression:

Here we apply a Random-effects regression.

Table 3.8-6 Random-effects regression

```
Random-effects GLS regression                   Number of obs      =     10366
Group variable: Idd                             Number of groups   =      1375

R-sq:  within  = 0.1458                         Obs per group: min =         1
       between = 0.0709                                        avg =       7.5
       overall = 0.0788                                        max =        13

                                                Wald chi2(3)       =   1135.26
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

MARET	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logME	-.0032555	.0038044	-0.86	0.392	-.010712	.004201
logBM	-.1965978	.0068281	-28.79	0.000	-.2099806	-.1832149
Fscore	.0363224	.0027919	13.01	0.000	.0308504	.0417944
_cons	-.2238358	.0286828	-7.80	0.000	-.2800529	-.1676186
sigma_u	.13233391					
sigma_e	.39791356					
rho	.09958781	(fraction of variance due to u_i)				

Choosing between the fixed and random-effects:

Greene (2008) said: “The crucial distinction between fixed and random-effects is whether the unobserved individual effect embodies elements that are correlated with the regressors in the model, not whether these effects are stochastic or not” (p. 183, *Econometric Analysis*).

Here we use the Hausman test:

H: $(\beta^{FE} - \beta^{RE})$ $[\text{var}(\beta^{FE}) - \text{var}(\beta^{RE})]^{-1}$ $(\beta^{RE} - \beta^{RE}) \approx \chi 2\ (K)$

Where $(\beta^{FE} - \beta^{RE})$ is the vector of the difference between the estimates of the coefficients from both the random and fixed-effects specifications and $[\text{var}(\beta^{FE}) - \text{var}(\beta^{RE})]^{-1}$ is the difference in their variances. The test is distributed as $\chi 2\ (K)$ with K equal to the number of coefficients of the model.

The hypothesis HO is that estimates by random-effects are not different from those for fixed-effects. Therefore, they are consistent and the random-effects should be preferred. The H1 hypothesis states that estimates by random-effects are different from those for fixed-effects. Therefore, they are not consistent and the random-effects estimators are not appropriate.

The Hausman test

Table 3.8-7 Hausman test

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
logME	.0013952	-.0032555	.0046507	.0086222
logBM	-.3673396	-.1965978	-.1707418	.0080159
Fscore	.0287256	.0363224	-.0075968	.0009602

b = consistent under Ho and Ha; obtained from xtreg
B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test: Ho: difference in coefficients not systematic

chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
= 652.80
Prob>chi2 = 0.0000

The Hausman test tests the null hypothesis that the coefficients estimated by the random-effects estimator are the same as the ones estimated by the fixed-effects estimator. If they are, then it is more suitable to use random-effects; however, if a statistically significant P-value is obtained, it is more suitable to use fixed-effects. The P-value is statistically significant therefore fixed-effects is more appropriate.

In that case we regressed: Model 3: $MARET_{it}$ = α + $\beta_0 \log(ME_{it})$+ $\beta_1 \log(BM_{it})$ + $\beta_3 Fscore_{it}$+ ε_{it} by restricting the year greater than or equal to 2007. The results show that all our variables are significant.

Fixed-effects regression when year is >= 2007

Table 3.8-8 Fixed-effects regression when year is greater than 2007

```
Fixed-effects (within) regression               Number of obs      =      4800
Group variable: Idd                             Number of groups   =      1018

R-sq:  within  = 0.1822                         Obs per group: min =         1
       between = 0.1148                                        avg =       4.7
       overall = 0.0820                                        max =         6

                                                F(3,3779)          =    280.71
corr(u_i, Xb)  = -0.7631                        Prob > F           =    0.0000

------------------------------------------------------------------------------
        MARET |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logME |   .1130538   .0185846     6.08   0.000      .076617    .1494905
        logBM |  -.3462165    .018918   -18.30   0.000     -.383307    -.309126
       Fscore |   .0201594   .0043167     4.67   0.000     .0116961    .0286227
        _cons |  -1.173742   .1355402    -8.66   0.000    -1.439481   -.9080029
-------------+----------------------------------------------------------------
      sigma_u |  .34817467
      sigma_e |  .36294747
          rho |  .47923504   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(1017, 3779) =     1.47          Prob > F = 0.0000
```

The model fits the data at the 0.05 significance level (F=280.71, p<0.000). The within R^2 of 0.1822 says that this model accounts for 18% of the total variance. The model has an intercept of -1.17 and slope of -0.34 for the logBM and 0.11 for the logME. Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 2% increase in the market-adjusted return. Notice that we have restricted the sample year to be 7 years.

Random-effects regression when year is >=2007

Table 3.8-9 Random-effects regression when year is greater than 2007

```
Random-effects GLS regression                   Number of obs      =      4800
Group variable: Idd                             Number of groups   =      1018

R-sq:  within  = 0.1603                         Obs per group: min =         1
       between = 0.1141                                        avg =       4.7
       overall = 0.0934                                        max =         6

                                                Wald chi2(3)       =    535.81
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

MARET	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logME	.0155481	.0044327	3.51	0.000	.0068602	.024236
logBM	-.1587805	.008487	-18.71	0.000	-.1754148	-.1421462
Fscore	.0283939	.0038987	7.28	0.000	.0207526	.0360353
_cons	-.3262804	.0349108	-9.35	0.000	-.3947042	-.2578566
sigma_u	.1037639					
sigma_e	.36294747					
rho	.07555868	(fraction of variance due to u_i)				

The model fits the data at the 0.05 significance level (F=535.81, p<0.000). The within R^2 of 0.1603 says that this model accounts for 16% of the total variance. The model has an intercept of -0.32 and slope of -0.158 for the logBM and 0.015 for the logME. Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 2.8% increase in the market-adjusted return. Notice that we have restricted the sample year to be before 2007.

The Hausman test

Table 3.8-10 Hausman test

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
logME	.1130538	.0155481	.0975057	.0180482
logBM	-.3462165	-.1587805	-.187436	.0169074
Fscore	.0201594	.0283939	-.0082345	.0018531

```
                  b = consistent under Ho and Ha; obtained from xtreg
   B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

            chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                    =      393.12
          Prob>chi2 =      0.0000
```

The Hausman test tests the null hypothesis that the coefficients estimated by the random-effects estimator are the same as the ones estimated by the fixed-effects estimator. If they are, then it is more suitable to use random-effects; however if a statistically significant P-value is obtained it is more suitable to use fixed-effects. The P-value is statistically significant therefore fixed-effects is more appropriate.

Fixed-effects regression when year is < = 2007

In this case we try to reproduce the same approach but here we are restricting the sample year as less than or equal to 2007. We run first a fixed-effects regression as previously applied.

Table 3.8-11 Fixed-effects regression when year is less than 2007

```
Fixed-effects (within) regression               Number of obs      =      6368
Group variable: Idd                             Number of groups   =      1170

R-sq:  within  = 0.1925                         Obs per group: min =         1
       between = 0.0499                                        avg =       5.4
       overall = 0.0662                                        max =         8

                                                F(3,5195)          =    412.84
corr(u_i, Xb)  = -0.7086                        Prob > F           =    0.0000

------------------------------------------------------------------------------
       MARET |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       logME |  -.0112671   .0145212    -0.78   0.438    -.0397347    .0172005
       logBM |  -.4872169    .016624   -29.31   0.000     -.519807   -.4546268
      Fscore |   .0277722   .0039065     7.11   0.000     .0201138    .0354306
       _cons |  -.3532244   .1038715    -3.40   0.001    -.5568561   -.1495926
-------------+----------------------------------------------------------------
     sigma_u |  .39888894
     sigma_e |   .4067862
         rho |  .49019889   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(1169, 5195) =     1.82          Prob > F = 0.0000
```

The model fits the data at the 0.05 significance level (F=412.84, p<0.000). The within R^2 of 0.1925 says that this model accounts for 19% of the total variance. The model has an intercept of -0.35 and slope of -0.48 for the logBM and -0.011 for the logME. Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 2.7% increase in the market-adjusted return. Notice that we have restricted the sample year to be after 2007.

Random-effects regression when year is <=2007

Table 3.8-12 Random-effects regression when year is less than 2007

```
Random-effects GLS regression                   Number of obs      =      6368
Group variable: Idd                             Number of groups   =      1170

R-sq:  within  = 0.1684                         Obs per group: min =         1
       between = 0.0693                                        avg =       5.4
       overall = 0.0766                                        max =         8

                                                Wald chi2(3)       =    716.39
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

MARET	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logME	-.0064309	.0051151	-1.26	0.209	-.0164563	.0035946
logBM	-.2154957	.0094791	-22.73	0.000	-.2340744	-.196917
Fscore	.0386061	.0036353	10.62	0.000	.031481	.0457311
_cons	-.2245135	.0380215	-5.90	0.000	-.2990342	-.1499928
sigma_u	.16353811					
sigma_e	.4067862					
rho	.13913615	(fraction of variance due to u_i)				

The model fits the data at the 0.05 significance level (F=716.39, p<0.000). The within R^2 of 0.1684 says that this model accounts for 16% of the total variance. The model has an intercept of -0.22 and slope of -0.21for the logBM and -0.006 for the logME. Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 3.8% increase in the market-adjusted return. Notice that we have restricted the sample year to be after 2007.

The Hausman test

Table 3.8-13 Hausman test

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
logME	-.0112671	-.0064309	-.0048362	.0135904
logBM	-.4872169	-.2154957	-.2717212	.0136567
Fscore	.0277722	.0386061	-.0108339	.0014302

```
                b = consistent under Ho and Ha; obtained from xtreg
 B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

              chi2(3) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                      =      606.41
            Prob>chi2 =      0.0000
```

The Hausman test tests the null hypothesis that the coefficients estimated by the random-effects estimator are the same as the ones estimated by the fixed-effects estimator. If they are, then it is more suitable to use random-effects; however if a statistically significant P-value is obtained it is more suitable to use fixed-effects. The P-value is statistically significant therefore fixed-effects is more appropriate.

Finally, we run the regression by excluding 2008 from our sample and by including new variables such as world q[65] and dividend yield and accruals. Even after including those variables, the F-score is significant.

[65] For each firm in country j, q is computed annually as total assets less the book value of equity plus market value of equity, all divided by book value of total assets. See for instance: Doidge et al. (2013).

Fixed-effects regression excluding 2008

Table 3.8-14 Fixed-effects regression excluding 2008

```
Fixed-effects (within) regression               Number of obs      =      9574
Group variable: Idd                             Number of groups   =      1372

R-sq:  within  = 0.1617                         Obs per group: min =         1
       between = 0.0560                                        avg =       7.0
       overall = 0.0710                                        max =        12

                                                F(6,8196)          =    263.52
corr(u_i, Xb)  = -0.6456                        Prob > F           =    0.0000

------------------------------------------------------------------------------
       MARET |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       logME |  -.0193915    .010219    -1.90   0.058    -.0394234    .0006404
       logBM |  -.4080228   .0116512   -35.02   0.000    -.4308621   -.3851835
      Fscore |   .0315601   .0031437    10.04   0.000     .0253976    .0377225
    Accruals |   .0974955   .0570245     1.71   0.087     -.014287     .209278
   Dividendy |  -.0046701   .0013609    -3.43   0.001    -.0073379   -.0020023
      Worldq |  -.0009837   .0001571    -6.26   0.000    -.0012917   -.0006757
       _cons |  -.2256265   .0763741    -2.95   0.003    -.3753391    -.075914
-------------+----------------------------------------------------------------
     sigma_u |  .33856387
     sigma_e |  .40419154
         rho |  .41232742   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(1371, 8196) =     1.77           Prob > F = 0.0000
```

The model fits the data at the 0.05 significance level (F=263.52, p<0.000). The within R^2 of 0.1617 says that this model accounts for 16% of the total variance. The model has an intercept of -0.22 and slope of -0.40 for the logBM and -0.019 for the logME.

Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 3.1% increase in the market-adjusted return. Notice that we have restricted the sample year by excluding 2008 to avoid the effect of the crisis.

Random-effects regression excluding 2008

Table 3.8-15 Random-effects regression excluding 2008

```
Random-effects GLS regression                   Number of obs      =      9574
Group variable: Idd                             Number of groups   =      1372

R-sq:  within  = 0.1460                         Obs per group: min =         1
       between = 0.0848                                        avg =       7.0
       overall = 0.0809                                        max =        12

                                                Wald chi2(6)       =   1073.07
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

MARET	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logME	-.0069427	.004051	-1.71	0.087	-.0148825	.0009972
logBM	-.2078523	.0075128	-27.67	0.000	-.2225772	-.1931274
Fscore	.0374146	.0029656	12.62	0.000	.0316022	.043227
Accruals	.2002356	.0428595	4.67	0.000	.1162326	.2842386
Dividendy	-.0039848	.0012617	-3.16	0.002	-.0064576	-.0015119
Worldq	-.0007705	.0001488	-5.18	0.000	-.0010621	-.0004789
_cons	-.1904722	.0313064	-6.08	0.000	-.2518315	-.1291128
sigma_u	.13881235					
sigma_e	.40419154					
rho	.1055021	(fraction of variance due to u_i)				

The model fits the data at the 0.05 significance level (F=1073.07, p<0.000). The within R^2 of 0.1460 says that this model accounts for 14% of the total variance. The model has an intercept of -0.19 and slope of -0.20 for the logBM and -0.0069 for the logME.

Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 3.7% increase in the market-adjusted return. Notice that we have restricted the sample year by excluding 2008 to avoid the effect of the crisis.

The Hausman test

Table 3.8-16 Hausman test

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
       logME |   -.0193915    -.0069427       -.0124488        .0093818
       logBM |   -.4080228    -.2078523       -.2001705        .0089055
      Fscore |    .0315601     .0374146       -.0058545        .0010432
    Accruals |    .0974955     .2002356       -.1027401        .0376147
   Dividendy |   -.0046701    -.0039848       -.0006854        .0005102
      Worldq |   -.0009837    -.0007705       -.0002132        .0000506
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      626.39
                Prob>chi2 =      0.0000
```

The Hausman test tests the null hypothesis that the coefficients estimated by the random-effects estimator are the same as the ones estimated by the fixed-effects estimator. If they are, then it is more suitable to use random-effects; however if a statistically significant P-value is obtained it is more suitable to use fixed-effects. The P-value is statistically significant therefore fixed-effects is more appropriate.

Fixed-effects regression including Altman Z-score

We run the regression by including a new variable such as Altman Z-score (1968) from our sample to see whether after including such a variable the F-score is still significant.

Table 3.8-17 Fixed-effects regression including Altman Z-score

```
Fixed-effects (within) regression               Number of obs      =     10366
Group variable: Idd                             Number of groups   =      1375

R-sq:  within  = 0.1588                         Obs per group: min =         1
       between = 0.0585                                        avg =       7.5
       overall = 0.0734                                        max =        13

                                                F(6,8985)          =    282.70
corr(u_i, Xb)  = -0.6421                        Prob > F           =    0.0000
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
logME	-.0039422	.0096239	-0.41	0.682	-.0228073	.014923
logBM	-.3670777	.0105274	-34.87	0.000	-.3877138	-.3464416
Fscore	.0281634	.0029577	9.52	0.000	.0223656	.0339611
Accruals	.0934948	.0492588	1.90	0.058	-.0030637	.1900533
Dividendy	-.0033679	.001214	-2.77	0.006	-.0057476	-.0009881
Zscore	-.0000273	.0000862	-0.32	0.751	-.0001962	.0001416
_cons	-.2954928	.0715838	-4.13	0.000	-.4358133	-.1551722
sigma_u	.31867552					
sigma_e	.39771748					
rho	.39099375	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(1374, 8985) =     1.69         Prob > F = 0.0000
```

The model fits the data at the 0.05 significance level (F=282.70, p<0.000). The within R^2 of 0.1588 says that this model accounts for 16% of the total variance. The model has an intercept of -0.29 and slope of -0.36 for the logBM and -0.0039 for the logME.

Coefficient of the F-score indicates that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 2.8% increase in the market-adjusted return.

Random-effects regression including Altman Z-score

Table 3.8-18 Random-effects regression including Altman Z-score

```
Random-effects GLS regression                   Number of obs      =     10366
Group variable: Idd                             Number of groups   =      1375

R-sq:  within  = 0.1446                         Obs per group: min =         1
       between = 0.0840                                        avg =       7.5
       overall = 0.0827                                        max =        13

                                                Wald chi2(6)       =   1169.46
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

MARET	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
logME	-.0049888	.0037975	-1.31	0.189	-.0124318	.0024542
logBM	-.1932178	.0068087	-28.38	0.000	-.2065626	-.179873
Fscore	.0351077	.0027957	12.56	0.000	.0296281	.0405872
Accruals	.2004822	.0385346	5.20	0.000	.1249559	.2760086
Dividendy	-.0035532	.00112	-3.17	0.002	-.0057483	-.0013581
Zscore	2.07e-06	.0000855	0.02	0.981	-.0001655	.0001697
_cons	-.1840978	.0292508	-6.29	0.000	-.2414284	-.1267673
sigma_u	.12903523					
sigma_e	.39771748					
rho	.09523628	(fraction of variance due to u_i)				

The model fits the data at the 0.05 significance level (F=1169.46, p<0.000). The within R^2 of 0.1446 says that this model accounts for 14% of the total variance. The model has an intercept of -0.18 and slope of -0.19 for the logBM and -0.0049 for the logME.

Coefficient of the F-score indicate that after controlling for size and book to market effects a one-point improvement in the aggregate score is associated with a 3.5% increase in the market-adjusted return.

The Hausman test

Table 3.8-19 Hausman test

```
. hausman fixed random

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |     fixed        random       Difference          S.E.
-------------+----------------------------------------------------------------
       logME |   -.0039422    -.0049888        .0010466         .008843
       logBM |   -.3670777    -.1932178       -.1738599        .0080292
      Fscore |    .0281634     .0351077       -.0069443        .0009653
    Accruals |    .0934948     .2004822       -.1069874        .0306842
   Dividendy |   -.0033679    -.0035532        .0001853        .0004685
      Zscore |   -.0000273     2.07e-06       -.0000294        .0000106
------------------------------------------------------------------------------
                          b = consistent under Ho and Ha; obtained from xtreg
           B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =      650.64
                Prob>chi2 =      0.0000
```

The Hausman test tests the null hypothesis that the coefficients estimated by the random-effects estimator are the same as the ones estimated by the fixed-effects estimator. If they are, then it is more suitable to use random-effects; however if a statistically significant P-value is obtained it is more suitable to use fixed-effects. The P-value is statistically significant therefore fixed-effects is more appropriate.

To conclude, most of the observations are clustered around F-score between 3 and 7, indicating that a vast majority of the firms have conflicting performances signals. Overall, the F-score is able to distinguish between winners and losers and enable us to follow to our next chapter by forming a market neutral portfolio.

3.9 Appendices

3.9.1 Appendix A: Bootstrapping results

Bootstrapping results for F-score and market-adjusted return; we are reporting results for the median, the 10th, the 25th, the 75th and 90th percentiles.

Table 3.9-1 Bootstrap regression by percentile

Bootstrap, Median regression

```
Median regression, bootstrap(1000) SEs             Number of obs =      15940
  Raw sum of deviations 4672.329 (about .021764)
  Min sum of deviations 4576.781                   Pseudo R2     =     0.0204
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0477151	.0025068	19.03	0.000	.0428015	.0526286
_cons	-.2190115	.01334	-16.42	0.000	-.2451595	-.1928635

Bootstrap, 10th percentile regression

```
.1 Quantile regression, bootstrap(1000) SEs        Number of obs =      15940
  Raw sum of deviations 1825.521 (about -.3561022)
  Min sum of deviations 1735.862                   Pseudo R2     =     0.0491
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0580095	.0021685	26.75	0.000	.0537589	.0622601
_cons	-.6266259	.0112841	-55.53	0.000	-.648744	-.6045079

Bootstrap, 25th percentile regression

```
.25 Quantile regression, bootstrap(1000) SEs       Number of obs =      15940
  Raw sum of deviations 3438.443 (about -.1761252)
  Min sum of deviations 3313.249                   Pseudo R2     =     0.0364
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0531238	.0018292	29.04	0.000	.0495383	.0567092
_cons	-.4371293	.0097589	-44.79	0.000	-.4562579	-.4180008

Bootstrap, 75th percentile regression

```
.75 Quantile regression, bootstrap(1000) SEs          Number of obs =      15940
  Raw sum of deviations 4310.587 (about .2489768)
  Min sum of deviations 4260.819                      Pseudo R2     =     0.0115
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0413774	.002635	15.70	0.000	.0362126	.0465422
_cons	.0353672	.013618	2.60	0.009	.0086745	.06206

Bootstrap, 90th percentile regression

```
.9 Quantile regression, bootstrap(1000) SEs           Number of obs =      15940
  Raw sum of deviations 2938.436 (about .5390507)
  Min sum of deviations 2925.341                      Pseudo R2     =     0.0045
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0366955	.0055511	6.61	0.000	.0258148	.0475763
_cons	.3490436	.0292635	11.93	0.000	.2916837	.4064034

Bootstrapping results for high F-score (7 to 9) minus low F-score (0 to 3); we are reporting results for the median, the 10th, the 25th, the 75th and 90th percentiles.

Bootstrap, Median regression

```
Median regression, bootstrap(1000) SEs                Number of obs =       5287
  Raw sum of deviations 1772.909 (about .0202045)
  Min sum of deviations 1697.274                      Pseudo R2     =     0.0427
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.047151	.0026919	17.52	0.000	.0418738	.0524283
_cons	-.2137694	.0155183	-13.78	0.000	-.2441917	-.1833471

Bootstrap, 10th percentile regression

```
.1 Quantile regression, bootstrap(1000) SEs           Number of obs =       5287
  Raw sum of deviations 677.8116 (about -.40560991)
  Min sum of deviations 613.9683                      Pseudo R2     =     0.0942
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0583231	.0024535	23.77	0.000	.0535132	.0631329
_cons	-.6384449	.0129595	-49.26	0.000	-.6638508	-.613039

Bootstrap, 25th percentile regression

```
.25 Quantile regression, bootstrap(1000) SEs          Number of obs =       5287
  Raw sum of deviations 1297.554 (about -.2031973)
  Min sum of deviations 1197.909                      Pseudo R2     =     0.0768
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0530312	.0021126	25.10	0.000	.0488897	.0571727
_cons	-.4505867	.0124385	-36.23	0.000	-.4749713	-.4262021

Bootstrap, 75th percentile regression

```
.75 Quantile regression, bootstrap(1000) SEs          Number of obs =       5287
  Raw sum of deviations 1640.119 (about .28460991)
  Min sum of deviations 1607.049                      Pseudo R2     =     0.0202
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0403074	.0035503	11.35	0.000	.0333473	.0472674
_cons	.0699443	.0201055	3.48	0.001	.0305292	.1093595

Bootstrap, 90th percentile regression

```
.9 Quantile regression, bootstrap(1000) SEs           Number of obs =       5287
  Raw sum of deviations 1122.974 (about .62379581)
  Min sum of deviations 1116.692                      Pseudo R2     =     0.0056
```

MARET	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
Fscore	.0289724	.0078588	3.69	0.000	.0135659	.0443789
_cons	.480058	.0424955	11.30	0.000	.3967492	.5633667

3.9.2 Appendix B: Time series number of companies by year and F-score

Table 3.9-2 Number of companies every year

Year	F0	F1	F2	F3	F4	F5	F6	F7	F8	F9	Low	High
2000	13	26	84	199	240	325	220	113	41	8	322	162
2001	10	15	84	171	217	342	277	114	40	4	280	158
2002	7	15	30	133	177	318	317	192	71	2	185	265
2003	6	19	55	131	204	293	335	171	43	4	211	218
2004	9	13	39	152	236	314	298	160	44	4	213	208
2005	9	15	51	171	217	324	312	132	30	4	246	166
2006	3	7	45	166	254	306	250	167	45	0	221	212
2007	5	15	32	157	217	326	294	135	45	2	209	182
2008	5	13	82	181	229	330	239	104	21	1	281	126
2009	3	5	21	100	144	343	334	210	57	4	129	271
2010	2	7	27	126	203	309	324	162	53	3	162	218
2011	7	11	43	147	235	368	256	109	23	1	208	133
2012	0	4	29	98	205	287	234	131	37	2	131	170

Chapter four – Implementing a market-neutral strategy

4.1 Introduction

Market neutral strategy is often associated as part of one of the strategies implemented among the long-short hedge fund strategy. Long-short equity strategies can be traced back to the late 1940s where undoubtedly the first hedge fund introduced in the literature started with W. Jones' investment partnership in 1949. Jones started to short sell securities in part to offset the systematic risk introduced by the long position in the portfolio. It was later refined by Nunzio Tartaglia at Morgan Stanley in the late 1980s, where he was known for his pair-trading strategies approach. Since the 1960s, the hedge fund industry has grown with the rise of star hedge fund managers such as George Soros and Julian Robertson.

The current form of most US hedge funds is now a limited partnership in which the investors are limited partners and the managers are general partners or a limited liability company established to invest in public securities. As general partners, the hedge fund managers invest a significant amount of their personal wealth to ensure the alignment of economic interests among the partners. Also, there has been a shift in the type of investor in hedge fund vehicles from an individual investor to an institutional investor, such as pension funds which invest in hedge funds for diversification purposes.

The market neutral equity strategy has started to become popular among practitioners since the end of 2000 within the tech bubble. Instead of correctly forecasting underlying market moves, market neutral strategies seek to profit from detecting mispricing in individual securities by constructing hedge portfolios that deliver the excess returns associated with those securities. Therefore, the main goal of this chapter is to apply a market neutral equity strategy to our Piotroski F-score. By consequence, the novelty of this chapter is to construct a market neutral portfolio using our F-score composite and if efficient this should shift the distribution earn by an investors. This has not been done in this way in the past and we highly believe that an investor and the literature can benefit from our findings.

The rest of the chapter is outlined as follows: the first part of the chapter gives a brief insight into the hedge fund industry given the recent rise in flows of money into the industry, and the second part summarizes the literature on the market neutral strategies and gives a broader picture of hedge funds in general. The third part of the chapter reviews the characteristics on the role of market neutral strategies, including benefits such as the diversification that can be obtained from implementing these strategies as well as the limitations. The fourth part describes different risk-adjusted performance measures used to assess our results. Finally, the last part presents the empirical results gained from implementing the strategy based on stocks selected by our model.

4.2 Hedge fund overview

In 2013, with reference to “Eurekahedge”, the hedge fund industry had a good rally, attracting $127.4 billion net asset flows, yielding the current assets under management of the industry at $1.99 trillion. Over the last thirteen years the hedge fund industry has advocated different patterns such as period of growth, downfall and period where the market bounced back.

Figure 4.2-1 below shows that the hedge fund industry has increased since 2000 where the assets under management were around $330 billion with more than 2000 funds. Until 2007, the hedge fund industry knew continuous growth in the assets managed and the flows of funds, leading the total industry to $1.95 trillion by mid-2008. The number of assets under management rebounded after the financial crisis due to a decline in performances and an outflow of money from investors worried about the turmoil. Since then, the industry has been going back towards the high of 2007 with 1.30 trillion of assets under management. Practitioners expect the industry to grow to $1.5 trillion by 2016 given the recent strong performance and downfall protection provided by hedge fund managers.

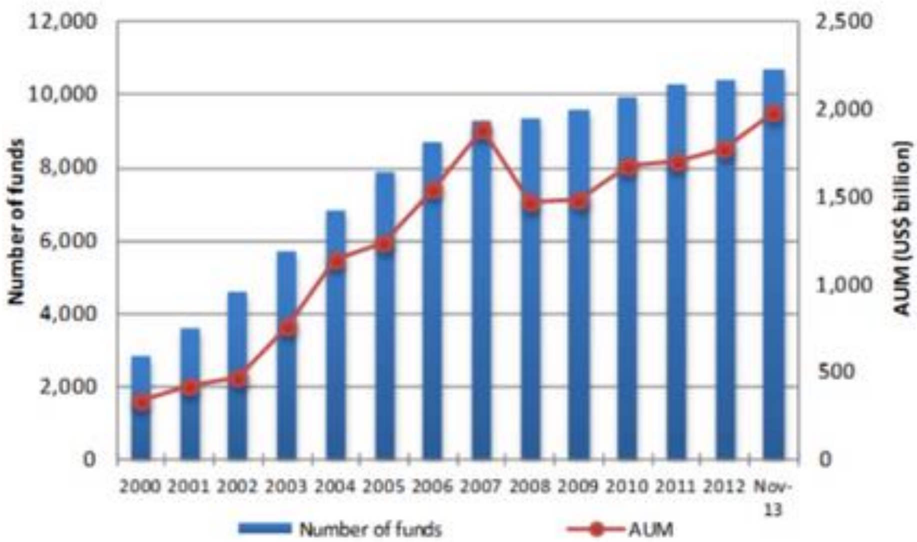

Figure 4.2-1 Industry growth over the years

Source: Eurekahedge(2013)

The graph in Figure 4.2-2 below describes the global hedge funds' performance since 2006 in $; there is roughly a 35% increase in performance between 2006 and 2013. The year 2009 describes the financial crisis where hedge funds had a decline in performance due to a big hit on the market.

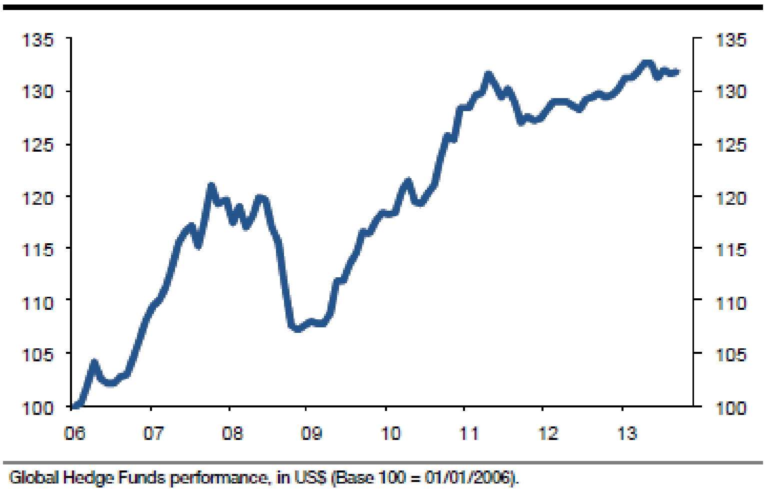

Figure 4.2-2 Global Hedge funds' performance

Source: Eurekahedge(2013)

Figure 4.2-3 provides some comprehension of strategies well used in the hedge fund industry and by number of assets under management. Asset flows were mixed among the various strategies with the long-short[66] equities seeing the largest percentage of global assets under management with 31.5%; the second biggest strategy used in the industry is the multi-strategy[67] with 15.4% of the global asset under management. Event driven[68], CTAs/Managed futures[69] and Macro[70] funds are well-used vehicles in the hedge fund industry with approximately 10% of global

---

[66] Buying long equities that are expected to increase in value and selling short equities that are expected to decrease in value

[67] The use of several strategies within the same pool of assets.

[68] Taking significant positions in companies with special situations.

[69] Going long or short in futures contracts in areas such as metal, grains, equity, and soft commodities as well as foreign currency and US government bond futures.

[70] Holdings primarily based on overall economic and political views of various countries.

assets under management each. Finally, fixed income[71] and arbitrage[72] strategies account for roughly 7% of the global assets under management.

Given the increasing interest in stock picking, investors expect the long-short equity strategy to attract more inflows of money with an estimated $67.1 billion attracted in 2013.

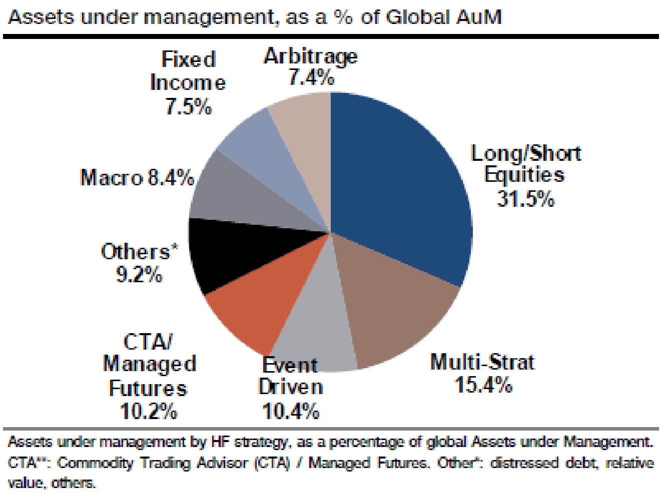

Figure 4.2-3 Assets under management expressed as a percentage

Source: Eurekahedge(2013)

4.3 Literature review

We review in this part a large literature on hedge fund performance including a comparison between long-short and long-only, correlation provided by using such vehicles, a cointegration technique, the alpha interpretations, the persistence in the performance of hedge funds, the risk and reward obtained from hedge funds, some diversification benefits – especially when used in a portfolio – and, finally, we review the survivorship bias.

[71] Exploits arbitrage opportunities in interest rate securities or it could be strategies concerning convertibles securities: buy convertibles long and sell the underlying stocks of the convertible short.

[72] Exploits the price differentials that exist as a result of market inefficiencies.

4.3.1 Long-short over long-only

Several studies have tried to understand long-short funds by comparing them to something more familiar, like long-only funds. Both of them are investment vehicles but the investment strategy differs from one to the other.

Long-only funds employ mainly buy-and-hold strategies, where they only take long positions in liquid assets and their returns are compared to a benchmark index. Hedge funds employ more dynamic trading strategies, where they take both long and short positions in sometimes liquid or illiquid assets and have an absolute return.

In one of the most comprehensive studies on long-short equity, Bruce and Levy (1995) examined various aspects of a long-short strategy, reporting three ways of implementing long-short equity: “market neutral”, which implies holding long and short in equal dollar balance; “equitized”, which suggests adding permanent stock index futures as well as holding stocks long and short in equal dollar balance; and the last way is through a “hedge strategies” based on implementing a variable equity market exposure such as stock index futures. Across their paper, they present the different aspects of implanting long-short strategies. Consistent with this approach, John and Miller (1996) suggested presenting a quantitative method to build a long-short portfolio using rules; the model has previously been reported to generate a 3.5% excess return per quarter.

BARRA RogersCasey (2000) presented a paper on the various advantages attached to the use of market neutral long-short equity strategies. The paper discusses both positive and negative aspect of market neutral investment strategy focusing especially on long-short equity market neutral strategies, and the ability for investors to generate higher return per unit of risk.

In a descriptive article, Michaud (1993) showed that, for any given level of risk, the return to a long-short strategy is associated with higher return than a long-only portfolio. As stated: “Long-short portfolio consisting of long positions in undervalued stocks and short positions in an equal value portfolio of overvalued stocks, where market risk is minimized can achieve twice the expected active return of the conventional long-only portfolio with minimal risk” (p. 44, *Are Long-Short Equity Strategies Superior?*). In addition, Liang (2000) found that hedge funds have higher returns than mutual funds. The average monthly return from 1992 to 1996 for hedge funds was 1.10% compared to 0.85% for mutual funds and the standard deviation was 2.40% for hedge funds and 1.91% for mutual funds.

There is some significant evidence that, even if the long-short funds appear to yield abnormal returns to investors, long-only funds – if efficiently driven – can dominate long-short strategies at levels of risk. When focusing on long-short strategies, investors are generally often over-optimistic about the characteristics obtained and the strategy can turn out to be much more risky. Liang (1999) found that hedge funds (long-short funds) have on average a higher Sharpe ratio than mutual funds (long-only funds). This means the mean-variance frontier is higher for hedge funds than for mutual funds. The benefits of using a long-short strategy instead of a long-only portfolio were discussed by Jacobs et al. (1999), who highlighted the different characteristics attributed to this strategy. For instance, the authors stated that: "A long-plus-short portfolio thus offers benefit over a long-only portfolio only if there is a less than one correlation between the alphas of its long and short sides. In that case the long plus short portfolio will enjoy greater diversification and reduced risk relative to a long only portfolio" (p. 24, *Long-Short Portfolio Management: An Integrated Approach*). Arnott et al. (1994) reassessed the long-short strategies, making the observation that if the correlation between long and short securities approaches 1 a long-short strategy may not considerably improve the characteristics of a long-only portfolio. See also Jacobs and Levy (1999) who, in a descriptive paper, reviewed 20 myths regarding long-short advantages against a simple long-only portfolio.

In summary, the extensive points of view regarding the ability of implementing a long-short strategy over a long-only one are not completely agreed upon among practitioners and it remains an investor's choice in his/her pursuit of risk and return.

4.3.2 Correlation

There is some evidence that hedge funds take beta bets to generate returns. Beta is the return of fund related to the exposure to different asset classes; investors would expect beta to be close to zero if the hedge funds manager tries to hedge out the risk in the market. A fund is said to be market neutral if it generates returns that are uncorrelated with the returns on some market indices.

Brooks and Kat (2001) revealed strong evidence of significant correlation of classic long-short equity hedge funds indices with equity market indices such as S&P500, Dow Jones, Russell 2000 and Nasdaq. Patton (2009) highlighted evidence against the neutrality to market risk of hedge funds, stating, for instance: "The most commonly used risk based definition of neutrality is based on correlation or beta: a fund may be said to be market neutral if it generates returns that are uncorrelated with the returns on some market index, or a collection of market risk factors".

(p. 2296, *Are Market Neutral Hedge Funds really Market Neutral?*), and concludes that many hedge funds that label themselves as market neutral are in fact not market neutral.

Liang (1999) found low correlation for hedge fund vehicles with the market using an eight-asset class factor model including factors like equity, debt, currency, commodities and cash. The low correlation indicates that hedge funds are less correlated with the market compared to traditional vehicles such as mutual funds. Using a return-based analysis, Fung and Hsieh (1997) found that mutual funds have high correlation with asset classes whereas hedge funds have low correlation.

Edwards and Caglayan (2001) examined the performance of hedge funds and commodity funds in bear and bull markets by looking at the correlation with the market. Sixteen different investment strategies used by hedge funds and commodity funds were analyzed, and the authors reached the conclusion that commodity funds provide greater downside protection than hedge funds and have generally an inverse correlation with stock returns in bear markets.

In addition, studies have suggested that hedge funds exhibit generally more positive correlation with stock returns in bear markets than in bull markets. Also, the market neutral, the event driven and the macro hedge fund strategies provide protection to investors during periods of downward trends on the stock market.

Schneeweis et al. (1996) suggested as well that the addition of CTAs (Commodity Trading Advisors or firm who provides individualized advice regarding the buying and selling of future contracts) to a portfolio due to its low return correlation can add value to it. This is in line with Markowitz (1952), who showed that investors can obtain steadier returns by combining assets with roughly similar expected returns but low correlation in the same portfolio.

Moreover, Schneeweis and Spurgin (2000) made a distinction between good, bad and stable correlation regarding if the correlation is high during periods when the market is up or compared during periods when the market is down due to different patterns in the market. Correlations between -0.3 and +0.3 are thought to be non-correlated, which means that the two asset classes move independently from each other, with non-correlated assets; when one is rising in price, the other may be rising, falling, or maintaining its current price.

In summary, a properly allocated portfolio has a mix of investments that do not behave the same way. To maximize the portfolio benefits derived from correlations, one would need to incorporate investments with negative correlations, low positive correlations, or even assets that have non-correlations.

4.3.3 Cointegration technique

Recent studies suggest that academicians try to develop new techniques when building strategies.

The cointegration technique was first introduced by Engle and Granger (1987). The method consists of finding long-term relations between assets. Another major contribution made in the literature about the cointegration technique was the one discussed by Johansen (1988), which allows testing for cointegration among more than two asset prices.

For instance, Alexander and Dimitriu (2002) suggested using a different approach – a cointegration technique instead of a correlation technique; the cointegration technique was revealed to produce good results by focusing on its key characteristics such as mean reverting and tracking error. Evidence has demonstrated that a better use of information is exploited by the cointegration technique, allowing for more flexibility in the design of various strategies. As an example, this technique is suitable for index tracking or even long-short strategies.

Focusing on the cointegration technique, Alexander and Dimitriu (2002) presented two applications of using cointegration technique-based trading strategies: an index tracking strategy and a long-short equity market neutral strategy, showing that the characteristics of the cointegration technique allow once again for a better use of the information contained in stock prices.

Also, Burgess (2003) used the cointegration method to hedge an equity portfolio. Moreover, Lin et al. (2006) developed a new statistical approach in order to exploit mispricing between two assets based on the cointegration technique.

Additionally, Smedts and Smedts (2006) investigated the investment dynamics employed by hedge fund managers using a rolling-over regression technique to capture the time variability present in the different strategies used among hedge fund managers, indicating that the inclusion of time variability is important as the risk exposures change over time.

Therefore, when forming a long-short strategy investors can refer to different techniques, in particular the cointegration technique highlighted here which enables a better understanding of the risk compared to more traditional metrics such as beta.

4.3.4 Alpha interpretation

Although there is evidence that hedge fund strategies display subsequent returns, also called "Alpha", the alpha is the return of the hedge fund that cannot be explained by exposure to systematic risk. It is generally referred to in the literature and by practitioners as return attributed to the manager's skills. See, for example, Alexander and Dimitriu (2002), who provided evidence that in the hedge fund industry alpha is a proxy for excess return to active management adjusted for risk (Jensen 1969).

Jacobs and Levy (1999) throughout their paper demonstrated that, once alpha is generated through the use of long-short market neutral strategies, it can be transported to other market instruments such as the use of derivatives. In order to transport alpha, investors can possibly use derivatives, for instance futures, as well as swap to exchange returns from, for example, small cap for large cap returns; alpha offers investors flexibility in pursuit of return and control of risk. For instance, in 1999, Jacobs and Levy said: "The investor's asset allocation decision comes down to a choice between sacrificing security selection return in favour of asset class performance, or sacrificing asset class performance in favour of security selection return." (p. 3, *Alpha Transport with Derivatives*).

In addition, Michaud (1993) advised investors that alpha can be dangerous: a strategy that offers two positive alphas can be attractive whereas two negative alphas can be painful for hedge fund managers. Smedts and Smedts (2006) questioned whether hedge fund managers are still able to generate alpha and found that they can still outperform the market partly due to successful market timing. Amenc and Martellini (2002) found that hedge funds' dispersion in alphas is very large and it is difficult to measure the dispersion with a degree of certainty.

Hence, hedge funds display interesting aspects, such as alpha generator attributable to the superior resources available to hedge funds manages. Even if hedge funds charge more fees, investing through them can improve an investor's utility.

4.3.5 Persistence in the performance of hedge funds

If the superior return of hedge funds is attributable to better manager skill then one would expect the same funds to have persistence in returns year after year.

Investors are therefore questioning the literature as to whether hedge funds are still delivering performances; see for instance Bares et al. (2001), who have analyzed whether the performance of hedge funds in delivering subsequent returns is persistent across different time windows. Using a non-parametric approach (Kernel or Bayesian models) over the period January

1992 to December 2000, they studied whether hedge fund managers added value to the performance delivered to investors by investigating different investment strategies and different time horizons.

Based on a different point of view, which stipulates that hedge funds may exhibit a higher degree of non-normality as well as a non-linear relationship with the stock markets, Kat and Amin (2003) developed a new approach using new dynamic trading-based performance measures instead of using the Sharpe ratio or even the Jensen alpha, suggesting that those traditional performance measures are no longer suitable to evaluate hedge fund performance. On the other hand, Agarwal and Naik (2004) examined the persistence of performance in hedge fund returns using a one-year moving average. Their results suggested that there is persistence in return by recreating the payoff distribution and compare the cost of the strategy with the price of a fund participation.

Previously, Agarwal and Naik (2000) had investigated the performance of returns in hedge funds using a multi-period framework, i.e. the performance of hedge funds is short term or long term. They examined short-term and long-term persistence by investigating their pre-fee and post-fee returns over quarterly, half year and yearly timeframe periods; also, the persistence was assessed by investigating the series of wins and losses for two, three and more consecutive time periods. They reached the conclusion that strong persistence can be noticed in the quarterly horizon and the persistence slowly starts to reduce when shifting towards yearly persistence, indicating that persistence among the hedge fund industry is primarily short term, in contrast with the finding of mutual funds or fund of funds where investors should preconize long-term persistence in the return up to two years. Additionally, they added that the persistence is sensitive to the return measurement interval: persistence decreases as the return measurement interval increases.

In addition, Baquero et al. (2005) suggested controlling for the look-ahead bias tests of persistence as standard persistence in hedge funds may be biased if the fund’s survival depends on historical performances. They have created by the use of information what would not have been known during the period analysed.

Edwards and Caglayan (2001) examined the persistence in hedge fund performance over the period January 1990 to August 1998 using alphas from a six-factor risk model(T-bill, HML, SMB, WML, long term debt corporate bond). Employing both a parametric and a non-parametric model they found persistence in the performance over one-year and two-year periods and suggested that the degree of persistence might vary with the investment strategy put in place. Also, Bares et al. (2003) appraised the persistence of hedge fund performance over short- and long-term horizons.

Ackerman et al. (1999) found that hedge funds earned better return than mutual fund over the period 1988 to 1995 despite hedge funds exhibiting more volatility than mutual funds. On the performance of hedge funds, Liang (1999) examined the relationship between hedge fund performance and fund characteristics such as the nature of watermark, hurdle rate[73], and leverage. The results compared hedge fund against mutual fund. By using an asset class factor model and a mean variance efficient analysis, the paper tried to provide deep insight among the evaluation of hedge funds in terms of performance and risk. Liang reached the conclusion that hedge funds dominate mutual funds in the mean-variance and are different from mutual funds in the way they display their strategy. The results also found significant difference between the return of hedge funds with high watermarks[74] and those without watermarks, and reveal as well that an incentive fee provides managers with strong incentive schemes; the higher the incentive fee, the better the fund performance.

Capocci and Hubner (2004) investigated hedge funds' performance levels and persistence using various asset-pricing models. In the 1980s performance measures were based on the CAPM like the Jensen's alpha (1969); it is with the recent interest in multi-factor models on the cross-sectional variations in stocks return that researchers have started to identify factors such as size, leverage, earnings/price, book to market, etc, as the US shows little relation to the betas of Sharpe (1964). Lintner (1965) stated, however, that there is no unanimously accepted model across the literature.

In the same manner, Capocci et al. (2005) tested the performance of hedge funds over a period of bullish and bearish market using the same methodology developed by Capocci and Hubner (2004) by applying a ten-factor composite performance model that appeared to achieve significant results. Their results indicated that most hedge funds outperformed the market during the whole period and no significant underperformances were observed during periods of downfall.

[73] Managers can collect incentive fees only if the cumulative returns can make up for previous losses and exceed the hurdle rate.
[74] A high watermark ensures that a fund manager does not get paid large sums for poor performances. For instance, if the fund manager loses money over a period, s/he must get the fund above the high watermark before receiving a performance bonus.

Furthermore, investigating hedge funds' performance through portfolio strategies that incorporate predictability in managerial skills, fund risk loading and benchmark returns was studied by Avramov et al. (2011). They examined the out-of-sample investment opportunity set and found that there exist subgroups of ex-ante identifiable hedge funds that can deliver subsequent return. The strategy of selecting those hedge funds based on the criteria set up are robust to various considerations such as backfill bias, incubation bias, illiquidity-induced serial correlation, fund fees, closed funds, alternative benchmark, etc.

Finally, by revisiting stylized facts about hedge funds Joenvaara et al. (2012) found evidence that on average hedge funds deliver economically and statistically abnormal return on an equal and value-weighted basis even after examining for different size, investment strategies and domiciles. Also, they suggested that hedge fund performance persists at annual horizons. Findings are in line with previous results suggested by Kosowski et al. (2007).

Koh et al. (2003) suggested exploring the persistence outside the US, by investigating persistence in the performance of hedge funds that invest in Asia and found that persistence occurs mainly at monthly horizons and at quarterly horizons.

To conclude, studies differ in the point of view regarding the persistence of performance in hedge funds; however, despite numerous studies using different approaches, the main caveats might be that hedge fund persistence in performance seems to be more present over a short-term window.

4.3.6 Risk-adjusted return

Several studies have made evident that the hedge fund industry has known different changes over the years; as an illustration, risk factor is certainly the one that has been subject to the biggest metamorphosis.

Market neutral funds actively seek to avoid major risk factors but take bets on relative price movements. Fung and Hsieh (1999) declared: "Market neutral funds refer to those funds that actively seek to avoid major risk factors, but take bets on relative price movements utilizing strategies such as long-short equity, stock index arbitrage, convertible bond arbitrage and fixed income arbitrage" (p. 10, *Is Mean Variance Analysis Applicable to Hedge Funds?*). By contrast with this idea, Michaud (1993) said that, for any given level of risk, long-short strategy can yield to higher risk. "Active returns are generally accompanied by increases in active risk" (p. 48, *Are Long-Short Equity Strategies Superior?*), emphasizing that long-only portfolios when used efficiently can dominate long-short strategies at level of risk. In other words, investors when forming a long-short strategy are generally over-optimistic about the characteristics obtained by the strategy, which is no more than a long-only portfolio with more risks.

Kat and Amin (2001) investigated whether hedge funds offer investors a superior risk-adjusted return trade-off and revealed that stand-alone hedge funds do not offer higher risk return. Understanding hedge fund risk extends much beyond a simple linear exposure to market risk; for instance, Amenc and Martillini (2002) stated that hedge funds are not only exposed to market risk, but are exposed to volatility risk, default risk and liquidity risk. Amenc et al. (2003) provided evidence that even hedge funds following a zero-beta non-directional approach are exposed to a variety of risks such as volatility risk, liquidity risk and credit risk.

Liang (2001) stated: "The year 1998 was a disaster for the hedge fund industry. On August 17, Russia defaulted on its ruble debt and domestic dollar debt causing a panic among investors and resulting In widened spreads between high quality debt and risky debt" (p. 14, *Hedge Funds' Performance: 1990-1999*). The impact of financial crisis on hedge funds has demonstrated that hedge funds were heavily affected, leading to high risk in the market. In fact, a couple of funds had to close because of poor performances.

Since then, the literature has tried to understand hedge fund risk. Fung and Hsieh (2001) presented a vast methodology to understand hedge fund risk by focusing on trend-following strategy; to do so they used CTAs[75] funds because they are said to be trend-following strategies. The goal of this article was to model how trend-followers' funds achieved returns and in consequence define the characteristics for assessing the systematic risk of their strategy. In a similar manner, Siegmann and Stefanova (2009) examined whether the inflows of money into the US stock market after 2003 had impacted hedge fund exposure to systematic risk. Systematic risk results from conditions, events and trends occurring outside the scope of the investment; investors should understand the rules to reduce the risk. Agarwal and Naik (2004) suggested that the expected tail losses identified by the mean variance can be underestimated by as high as 54% compared with M-CVaR optimal portfolios, suggesting that ignoring the tail risk of hedge funds can result in significantly higher losses during market downturns.

Ackerman et al. (1999) examined the components that suggested hedge funds are more risky than mutual funds by providing insights analysis. Also, they provided significant results that US hedge funds could be more risky than offshore hedge funds even after controlling for

[75] CTAs are individuals or trading organizations registered with the Commodity Futures Trading Commission (CFTC) through membership in the National Futures Association, who trade primarily futures contracts on behalf of a customer.

differences in the categories. Cassar and Gerakos (2011) examined the determinants and effectiveness of methods that hedge funds use to manage portfolio risk and revealed that risk management practices are a function of hedge fund characteristics, such as leverage, number of positions and the capital invested. Also, they found that hedge funds that did use normal portfolio risk metrics did well during the 2008 crisis. Billio et al. (2012) examined dynamic risk exposure of hedge funds to various risk factors during different market volatility conditions using the regime-switching beta model. They find that during times of high volatility in the market most of the strategies are negatively exposed to the large-small and credit spread risk and change in VIX (volatility index), suggesting that liquidity risk and credit risk are common factors in downturn of the market. Indeed, these factors are important in accessing hedge fund risk during downturn in the market. Solely, exposure can be different during up or down markets.

Several studies have observed that hedge funds are important providers of risk-adjusted performances. Brown et al. (1999) examined the performance of offshore hedge funds over the period 1989 to 1995, using a database that includes both delisted funds and currently operating funds, by investigating whether the returns to hedge fund investors are predictable from past reported returns. When investigating this pool of offshore funds, they found significant results regarding positive risk-adjusted performance measure by the Sharpe ratios[76] and by Jensen's alpha[77].

Liang (2000) found that hedge funds have a higher Sharpe ratio than mutual funds. The average Sharpe ratio was 0.44 for hedge funds compared to 0.26 for mutual funds. Ackermann et al. (1999) also found that the average Sharpe ratio for hedge funds is higher than for mutual funds and reported a figure of 21% higher. Furthermore, there is evidence that hedge funds are important providers of liquidity in various financial markets. Siegmann and Stefanova (2011) found a positive relationship between market illiquidity and the market exposure prior to 2003 for hedge funds. As stated: "Before 2003, hedge fund acted as suppliers of liquidity, having a higher market exposure when stocks are undervalued due to low liquidity" (p. 20, *Market Liquidity and Exposure of Hedge Funds*).

Also, Boyson et al. (2010) examined evidence that hedge fund contagion can be linked to liquidity shocks, whilst Bekaert et al. (2005) said contagion can be defined as: "Correlation over

[76] Sharpe ratio is a measure of risk used to evaluate fund performances; the higher the Sharpe ratio the better are the fund risk-adjusted returns.
[77] Jensen's alpha is the difference between a series and its expected return on the market; in other words, it is the excess return above the market.

and above what one would expect from economic fundamentals" (p. 66, *Market Integration and Contagion*).

Recently, Ribeiro and Santos (2011) examined whether market neutral strategies are exposed to the equity market and if so whether they are in part neutral to that market. Using data from January 1998 to December 2008 they formed an analysis of market neutral strategies. To do so, they examined what kind of strategies consistently outperform over time considering four strategies of market neutral hedge funds. Their results suggested that the strategy does not perform differently than the traditional capital market, suggesting that the neutrality given by hedge funds is not entirely accurate. Also, they stated: "Our results lead us to conclude that arbitrage and pure alpha strategies in hedge funds are not as accurate as their name and investment styles may imply, and their neutrality facing the securities market seems compromised" (p. 20, *Market Neutral Hedge Funds Strategies: Are they Really Neutral?*).

The authors also added a critical view to the neutrality displayed by hedge funds suggesting that diversified hedge funds are not market neutral; during the period under review the strategy exhibited significant market exposure. Despite market neutral, event driven, macro and short selling types of hedge funds performing reasonably well during periods of downturn in the market, commodity funds can offer greater insights during a bear market.

In short, risk measures including illiquidity risk exposure are a challenge for hedge funds. Despite the fact that systematic risk is likely to increase, in the future hedge funds managers would have to develop new techniques in order to fully understand the constituents of the market.

4.3.7 Diversification benefits

There is evidence that hedge funds are important providers of diversification when used in a portfolio. Kat and Amin (2001) found that when hedge funds are used in a portfolio investors can benefit from the diversification of such a vehicles. Sharing the same idea, Amenc et al. (2003) found strong benefits associated with the used of hedge funds in a portfolio to obtain various diversification. Ackermann et al. (1999) suggested that the low beta values on hedge funds make them a potentially valuable addition to many investor portfolios. Empirical studies have highlighted the characteristics of dynamic trading strategies. Fung and Hsieh (1997) applied a Sharpe's style analysis to a large sample of hedge funds and CTAs, suggesting that the incorporation of hedge funds in a portfolio could significantly improve its risk-return profile. Amenc and Martellini (2002) found that the inclusion of hedge funds in a portfolio can significantly decrease the volatility of the portfolio without leading to a significant change in the return.

Lhabitant and Learned (2002) suggested building equally weighted portfolios of randomly selected hedge funds and showed that diversification works well in a mean variance space. Increasing the number of hedge funds in a portfolio decreases the portfolio's volatility while maintaining its average return level. Also, downside risk is reduced in a larger-sized hedge fund portfolio. Additionally, Hagelin and Promberg (2003) examined the returns and investment policies for portfolios of stocks and bonds with and without hedge funds. They found that the gains from adding hedge funds to a portfolio of stocks and bonds were statistically significant for most of the strategies involved.

Capocci (2006) investigated the exposure to the equity market for market neutral funds covering a sample period from January 1993 to December 2002. The author suggested that the top and bottom deciles funds have the highest market exposure to equity but most market neutral funds are not significantly exposed to the equity market. Fung and Hsieh (1999) added that a strategy is said to be market neutral if it generates returns which are independent of the relevant market returns.

Accordingly, Patton (2009) has presented evidence against the neutrality to market risk for hedge funds by testing different concepts of neutrality to capture the exposure of those funds. "The methods proposed in this paper may be interpreted as tests of the purity of the portable alpha strategy" (p. 2297, *Are Market Neutral Hedge Funds really Market Neutral?*). The results suggest that many of those hedge funds are not market neutral even if they are said to be "market neutral" but in some extent, compared to other types of hedge funds, they are market neutral; however, different points of view are exposed in this paper; only one-quarter of hedge funds in the market neutral category are significantly non-neutral at the 0.05 level significant.

Therefore, the full diversification that investors seek and rely on by investing in hedge funds may not be as efficient as supposed. As stated: "The dependence between hedge fund returns and market returns is often significant and positive, even for market neutral funds. The widely cited diversification benefits from investing in hedge funds thus may not be as great as first thought" (p. 2526, *Are Market Neutral Hedge Funds really Market Neutral?*). Market neutral strategies are known to present interesting properties such as low exposure and relatively low volatility, which can help investors to diversify their portfolio.

4.3.8 Survivorship bias

Given that hedge fund managers are not required to report data on their performance, there are some natural biases in all hedge fund databases.

We would like to finish this literature review by focusing on survivorship bias. Liang (2000) examined survivorship bias in hedge fund returns by comparing two databases. He found that survivorship bias exceeds 2% per year partly due to the fact that major hedge fund databases contain different amounts of dissolved funds and started to cover dissolved funds in 1994. The author studied as well survivorship by investment styles and found that biases are different across styles.

Fund and Hsieh (1997) found that the inclusion of defunct funds helps guard against "survivorship bias" in the case of estimating returns of trend-following trading style. Schneeweis et al. (1996) analyzed the differential risk return performance of survivor and nonsurvivor CTA and, using both cross-sectional and traditional abnormal return methodology, revealed that the return differential between survivor and nonsurvivor is due primarily to underperformance in the months prior to the dissolution; however, the impact of using a database that contains survivor bias has only a minor impact on traditional measures of risk and return performance.

Additionally, Malkiel and Saha (2005) analyzed potential bias that can influence measures of hedge fund performance. They showed that the practice of voluntary reporting and the adjournment of only favourable past results can cause returns calculated from hedge fund databases to be biased. They found that after correcting for the bias hedge funds have a lower return than the one reported, suggesting the importance for investors to take this caveat into account when selecting hedge funds.

In summary, hedge fund databases can potentially suffer from several of these biases, which can have a significant impact on the performance measures.

4.4 Characteristics of market neutral strategies

In a market neutral equity strategy, the investor buys expected winners that are supposed to do well over the investment horizon and sells short losers that are expected to perform poorly. In other words, a market neutral equity strategy holds long[78] stocks that are expected to appreciate in value and sells short[79] a roughly equivalent amount of stocks that are expected to perform poorly.

As an example, in a well-constructed market neutral portfolio, if you are long one dollar, you will be short one dollar, leaving no dollars exposed to the market. In the case stocks are behaving as expected with the long outperforming the shorts, this spread[80] will result in a positive return from security selection.

Because of this occurrence of buying and selling, market neutral strategies are often named "arbitrage" strategies.

The chart below in Figure 4.4-1 is for illustrative purposes and shows how hedge fund managers implement long and short positions in an attempt to offset market risk exposure. For example, returns would be positive in rising markets in the case longs rise more than shorts and returns would be positive in declining markets if longs fall less than shorts. We present three states of the market, a rising market, a declining market and, finally, a flat market. As can be noticed in each case the strategy enables investors to make profits regarding market conditions.

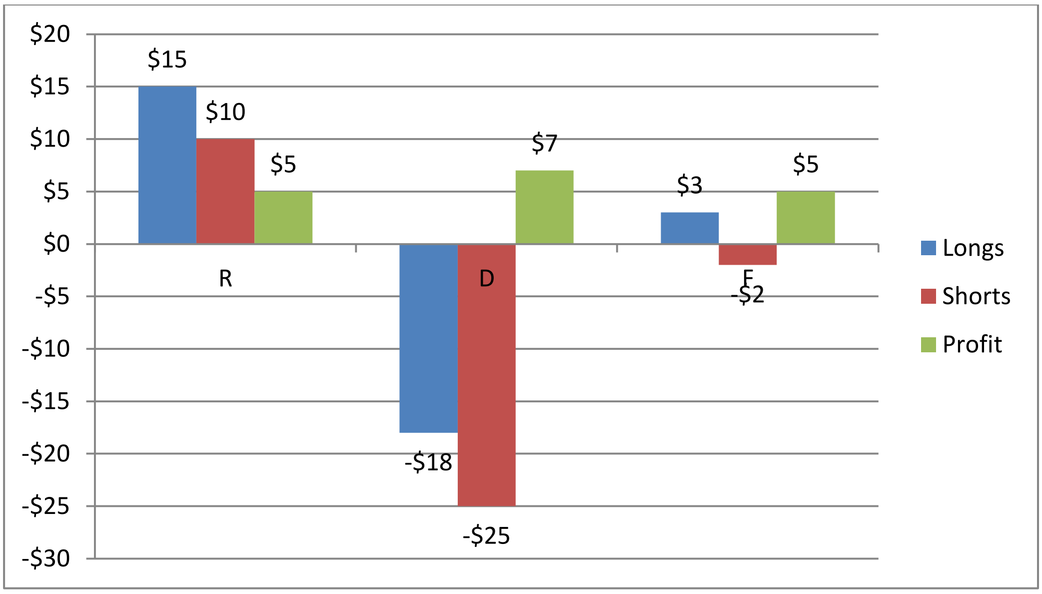

Figure 4.4-1 Hypothetical $100 investment in various market conditions

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[78] The long position, where the investor is a buyer of stocks: in this case the investor can benefit from profits when the stocks in the portfolio rise and lose when the stocks' prices fall.

[79] The short position, where the investors borrow stocks from another lender and then sells the stocks to generate the short portfolio. In this portfolio (short) the investors make profits when the prices of the constituents fall and lose when these stocks rise in price.

[80] Market neutral equity strategy only makes sense if pricing inefficiencies are larger or more frequent for potential short positions, i.e. among stocks that tend to be overpriced than for stocks that tend to be under-priced.

"R" defines a rising market condition, "D" a declining market and "F" a flat market.

Market neutral strategies are often used as a tool for diversification to the extent that they neutralize underlying market risk; in fact, they are said to be market neutral strategy to the point that they generate returns that are uncorrelated with the returns on some markets or other risk factors such as interest rate, liquidity and volatility. Therefore, investors would expect the beta with respect to the market to be close to zero if they hedge out the market risk. In this case of integrating market neutral hedge funds as well as convertible arbitrage, fixed income arbitrage or short selling, investors will benefit from a decrease in the portfolio volatility due to the low exposure of those strategies to the market risk.

By contrast, some hedge funds exhibit a high level of correlation[81] with the market, and offer returns that are relatively high. Adding that type of fund to a portfolio asset allocation made of equity and bonds would result in an increase in the expected return while retaining a high degree of volatility.

Also, trading a market neutral equity portfolio is said to be more complicated than trading a long-only portfolio; despite statistical models using a number of factors such as correlation and beta to help them determine how much equity to purchase or to sell short, managing a market neutral strategy remains an active management.

Indeed, the values and market sensitivities of the aggregate long and aggregate short positions must be kept in balance on a real-time basis in order to provide market neutrality. If imbalances occur, the hedge fund is open to a minimum amount of market risk and in consequence may have to sell long or shorts stocks covered until balance is restored. Derivatives may also be used to correct temporary imbalances.

Therefore, correlations are a key factor to take into account when rebalancing and trading a market neutral strategy. However, the success of a market neutral strategy depends merely on picking stocks, also called in the industry "seeking alpha". Most people think of alpha in terms of excess return relative to an underlying market but, in the hedge fund industry, alpha is a proxy for excess return to active management with all factors said to be neutral; the only issue

[81] Correlation is the technical term used to measure and describe how closely the prices of two investments move together over time. Positively correlated assets move in the same direction, both up or down, and negatively correlated assets move in the opposite directions. Correlations between two assets are scaled between +1 and -1.

that should remain is whether the portfolio manager is good at stock picking[82] – both long and short.

Thus, the overall return to a market neutral equity strategy has two components: an interest component and an equity component. The performances of the stocks held long and sold short will determine the equity component and an interest component received on the cash proceeds from the short sales.

The return is defined as the difference between the long and short portfolios such as

$$\mathrm{R_{LS}} = \mathrm{R_L} - \mathrm{R_S}$$

Where $\mathrm{R_L}$ and $\mathrm{R_S}$ denote the excess returns of the long and short portfolios.

Hedge fund managers when maintaining their market neutral strategy have at their disposal a liquidity buffer. The liquidity buffer serves as a pool to meet cash demands on account and, in general, a liquidity buffer equal to 10% of the initial investment. The liquidity buffer may also be used to reimburse stock lenders for any dividends paid on the short positions even if in most cases these payments can be made from the dividends on the long positions.

For hedge funds managers looking to maximize their bets, leverage is usually employed to purchase more of the investment and sell short more of the market. The results of the security selection are thus magnified. By increasing the size a position in a strategy can take, hedge fund managers are subsequently increasing the risk taken but, as well as the return in the case that the strategy is performing well, the effect results in more money invested than its original capital.

In summary, the risk of the strategy will depend on the degree of leverage employed.

Long-short equity displays interesting aspects such as being independent of market direction and uncorrelated to major asset classes; in addition, the strategy utilizes information more efficiently leading to higher alpha per unit of risk. When a portfolio combines equal long and short positions, stock picking becomes the main driver of performance. In consequence, the strategy will depend merely on how successful the manager is at selecting longs likely to appreciate more rapidly in rising markets and shorts that are more likely to decline faster in falling markets.

[82] Ability of the hedge fund manager to always identify stocks that s/he believes are either overvalued or undervalued.

Using long buys and shorts sells to take offsetting positions in a specific sector or industry is known as hedging. For example, a manager may hedge exposure to the health care sector by purchasing long health care stocks expected to perform well and selling short health care stocks expected to perform poorly. This strategy seeks to reduce overall portfolio risk and enhance return potential by neutralizing exposure to broad market movements, also called “beta”. Performance correlations are a critical factor to consider when building a diversified portfolio; as an illustration, negative correlations make excellent diversification allowing investors to pursue increased returns from assets that respond differently to changing conditions.

To conclude, we describe briefly the characteristics displayed by a market neutral strategy; we try to present a long plus short strategy following risk-adjusted property of the market neutral strategy. Solely, results appear to reflect a much more risky portfolio rewarded with greater returns.

4.5 Risk-adjusted performance measures

Higher returns are usually associated with higher risks; in this part we describe in detail measures used to evaluate the strategy such as Sharpe ratio, Information ratio, Maximum drawdown, Treynor ratio and the Sortino ratio.

Information ratio:

The Information ratio is a widely used measure among academicians and practitioners which provides investors with an idea of how the strategy is performing; an annualized Information ratio of 2 means that the strategy is performing well almost every month.

Information ratio is calculated as:

$$Annualized\ Information\ ratio = \frac{R}{\sigma}$$

Where R is the average return obtained from the strategy and σ is the standard deviation of return of the strategy. Both are calculated using the same time frame, in our case 252 trading days.

Sharpe ratio:

The Sharpe ratio is the best-known risk-adjusted return ratio introduced by Sharpe (1966) and differs from the Information ratio by adding a risk-free rate in the numerator.

The Sharpe ratio is a reward to variability ratio and is defined for any portfolio as:

$$Sharpe\ ratio = \frac{R - r}{\sigma}$$

Where R is the expected return on portfolio, σ is the standard deviation of return or the variance of the portfolio and r is the risk-free rate.

The Sharpe ratio measures the slope of the risk-free assets and is widely used to compare alternative strategies such as stock picking or market timing with passive strategies such as tracking the S&P 1500 and to compare the performance of different portfolio strategies.

Maximum drawdown:

The maximum drawdown is another indicator of the risk taken by a portfolio. It measures the largest single drop in the value of a portfolio an investor can suffer if s/he enters the market at the worst time. Maximum drawdown is an ex-ante proxy for downside risk that computes the largest drawdown over all intervals of time that can be formed within a specified interval of time.

It is defined as:

$$Min\left[r_t - max\left(\sum_{t=1}^{n} r_t\right)\right]$$

Treynor ratio:

The Treynor ratio was first introduced by Treynor (1965) in an attempt to measure how well an investment has compensated its investors given its level of risk. The higher the Treynor ratio the better the performance of the portfolio or stock being analyzed. It is a widely used measure of market-related risk in a stock or collection of stocks.

It is defined as:

$$Treynor\ ratio = \frac{ER_i - r}{\beta_i}$$

It is a measure of the ex-ante excess return per unit of risk but this time the risk is measured by the incremental portfolio risk given by the portfolio-beta. Similar to the Sharpe ratio, the Treynor ratio is used to compare performance of different alternative portfolios and the best portfolio is defined as that with the highest Treynor ratio.

Sortino ratio:

The Sortino ratio is a modification of the Sharpe ratio in the sense that, instead of considering the general volatility in a portfolio, the Sortino ratio focuses only on the downside volatility. A large Sortino ratio indicates that there is a low chance of a large loss occurring in the portfolio.

It is defined as:

$$Sortino\ Ratio = \frac{R - r}{\sigma_d}$$

Where R is the expected return on portfolio, σ_d is the standard deviation of negative asset return and r is the risk-free rate.

4.6 Empirical results

We start this part by demonstrating how we combine a list of stocks generated by our Piotroski F-score model and CRSP for stock and market index return information.

The code starts by matching our company list with the CRSP Permco[83] identifier using primary issue identifier Linkscore to resolve duplicate links. Then we get daily stock data and add market return. Keeping only common stock identified by CRSP as share code (10, 11) we calculate

[83] A unique permanent identifier assigned by CRSP to all companies with issues on a CRSP file. This number is permanent for all securities issued by this company regardless of name changes.

daily return over a one-year period starting 90 days after fiscal period year-end to ensure that the necessary annual financial information is available to investors at the time of portfolio formation; this correspond roughly to the annual report filing date, expected to be within 90 days of the fiscal period end.

Also, returns are calculated including distributions as a value-weighted return. CRSP[84] tracks all securities listed on the NYSE, AMEX, ARCA and NASDAQ exchanges and results were obtained for the period 1991 to 2012.

Here in Figure 4.6-1 is an example of the return retrieved from the database:

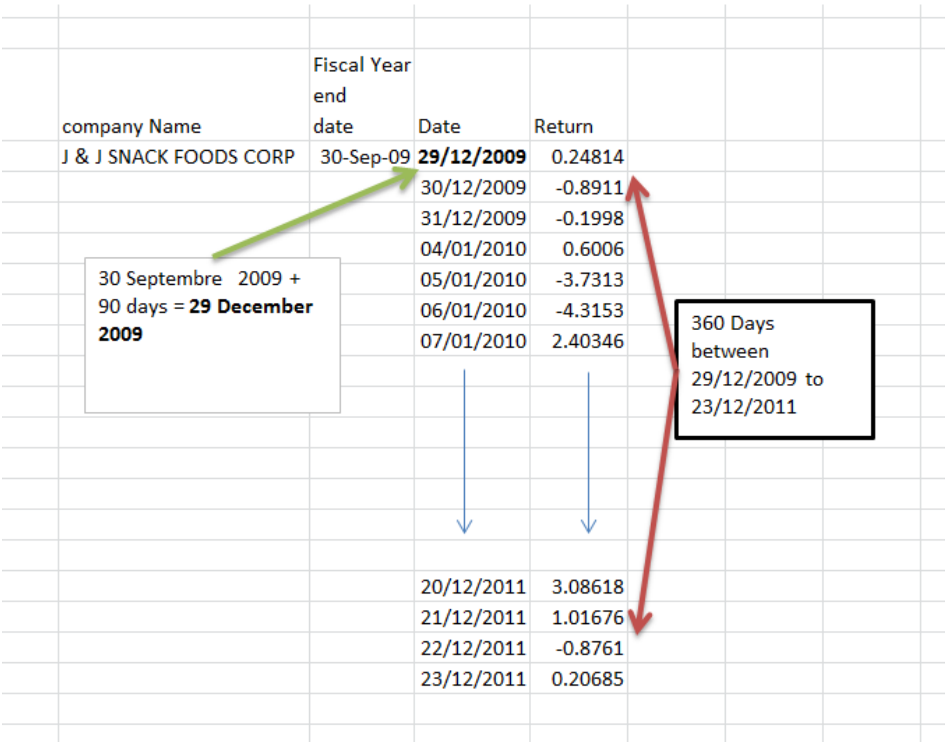

Figure 4.6-1 Example of how we extract data from CRSP

[84] CRSP provides the date of delisting return and the classification code of the event type. "After a security has been removed from the exchange, CRSP calculate a delisting return of this security by comparing the security's value after it delists with its price on the last day of trading. The value after delisting can be an off-exchange price, an off-exchange bid-ask spread, or the sum of a series of distribution payments". In order to avoid biases, incorporating delisting returns would help to assess components of any portfolio more accurately.

The objective of this part is to achieve a market neutral strategy by investing in companies, primarily based on our Piotroski replication model. To do so, we are creating two portfolios, i.e. a long portfolio with stocks ranked above 7. In other words, we constitute a portfolio of high Piotroski with scores of 7 to 9. The same approach is taken for the short portfolio except in that case we are creating a portfolio of low Piotroski scores of 0 to 3.

The reference benchmark for the long-short market neutral strategy is the S&P 1500 index only used for indicative purposes. As the long-short portfolio follows an unconstrained strategy, returns and risk metrics will differ from the one expected by a pure market neutral strategy.

We believe that holding stocks on a rolling three-year basis the strategy would not deliver an annualized excess return versus the benchmark; however, we define an investment window of 3 months, 7 months and 12 months for investors willing to benefit from our strategy. The purpose is to highlight that our strategy is more accurate in a short-term window, especially on a 3-month window, as it is limiting the downside risk and delivering great returns.

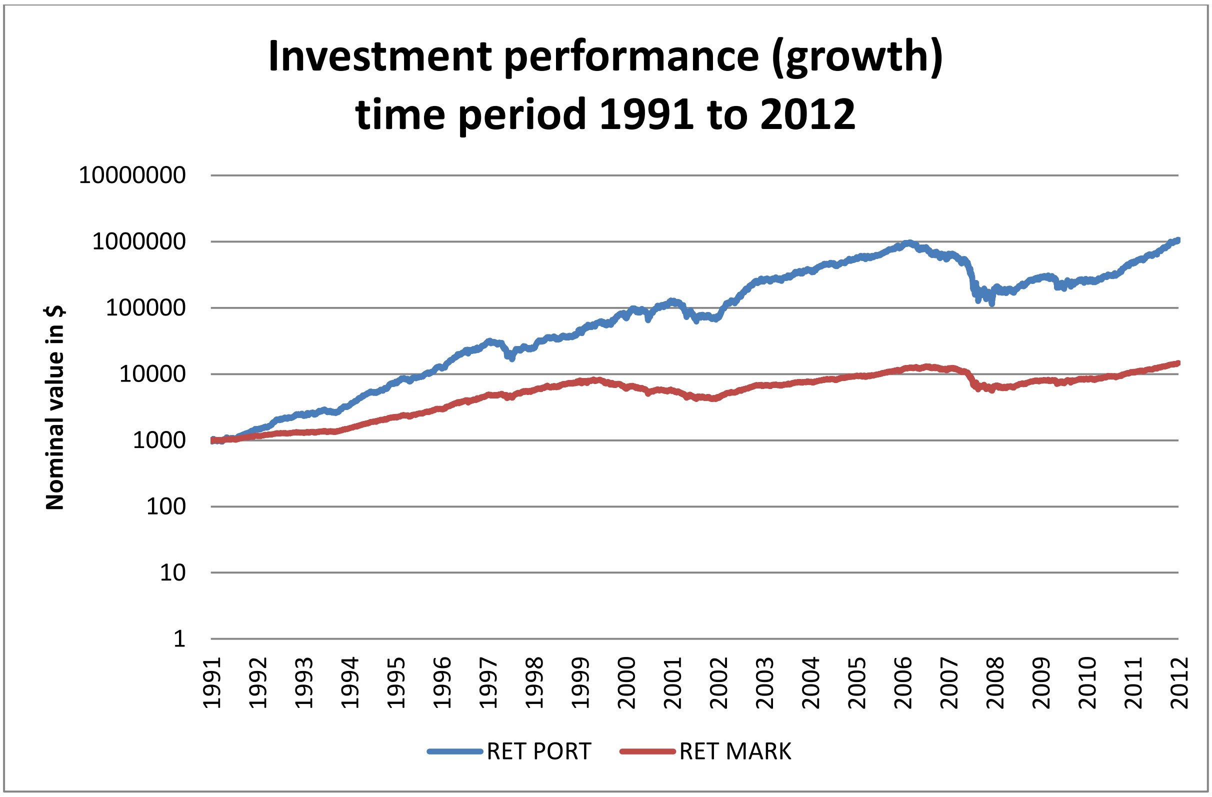

Figure 4.6-2 Investment performance from 2008 to 2012 formulated on a 12-month window

The graph in Figure 4.6-2 above represents the cumulative performance over 22 years in dollars. It shows the value as of beginning of fiscal year 1991 of a $1,000 investment made on our portfolio when we are holding stocks on a 12-month basis. For comparative purposes, the performance of the S&P 1500 index is used as a benchmark.

We show that the strategy has outperformed the benchmark over the long term, by delivering an alpha investment. This market neutral strategy has demonstrated skills across the market cycle and this approach gives the portfolio a higher risk profile than the benchmark but with considerably greater returns. However, this past performance should not be taken as an indication of future performance, which will vary according to market conditions; as we demonstrate later, the strategy appears to underperform during pre-crisis time. Over the past 22 years an investor who would have invested $1,000 in our portfolio would be worth more or less $1,000,000.

We feel that our replication of the Piotroski score allows us to distinguish between high-quality stocks and distressed stocks, supporting us to differentiate ourselves from the competition, which will enable us to outperform in most market conditions. One of the environments in which our portfolio will tend to underperform is during a “pre-crisis” market. The primary reason for this is that we use a fundamentally stock-picking approach providing a “double alpha” play and if the market is in an euphoric state, i.e. the volatility is high, then we will be likely to underperform the benchmark.

4.6.1 Excess return

In this part, we describe the excess return obtained when forming a long-short market neutral strategy. Three time windows are presented: 12 months, 7 months and 3 months.

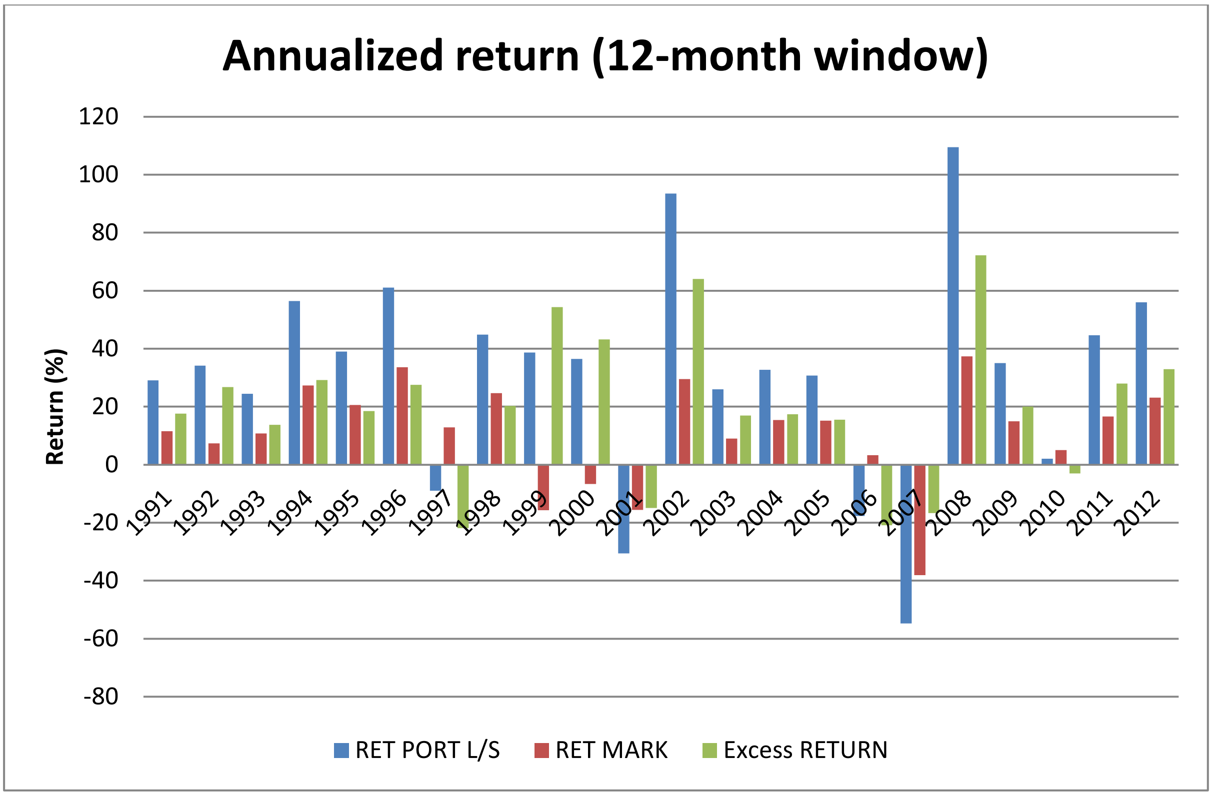

Figure 4.6-3 Long-short portfolio versus the market across a 12-month window

In Figure 4.6-3, we display the long-short portfolio annual performance in returns for each fiscal year over the period shown in the chart, i.e. from 1991 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark, which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for five periods out of twenty-two. In other words, this means that investors would have above a 77% chance that we will return money if they were investing in our strategy over a 12-month window.

From each down period the strategy long-short seems to react well as we recover from massive losses. The strategy performed particularly well in the crisis years of 2002, 2008 and 2011 with gains of +93.53%, +109.49% and +44.46% over these three years compared with 29.52%, 37.34% and 5.01% respectively for the benchmark S&P 1500. In 2012 the strategy has outperformed with 56.02%, compared with 23.14% for the benchmark S&P 1500. The excess return earned above the market is about 32.89%. (Refer to Appendix A).

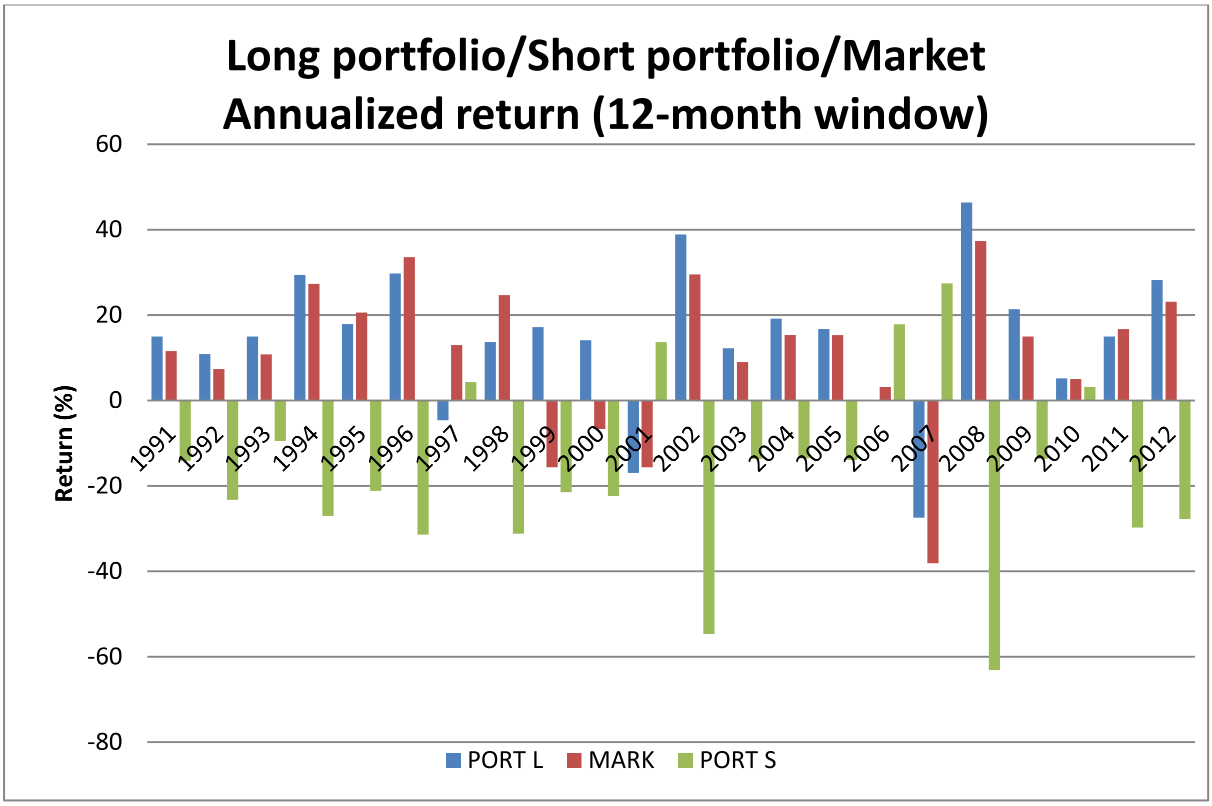

Figure 4.6-4 Details of the return that constitutes our long-short strategy (12-month window)

In Figure 4.6-4, we show graphically how each portfolio is doing over the benchmark S&P 1500. The idea is to highlight years where perhaps we could have increased weights in one of the two portfolios, long or short.

In 1993 the long portfolio has generated 14.95% and the short portfolio -9.51% versus 10.56% for the benchmark S&P 1500. This results overall in an excess return of 13.70%. The same can be described for the year 2001, where the long portfolio is underperforming as well as the short portfolio. During that year the long portfolio has returned -16.97% whilst the short portfolio has returned +13.59%, leading to a long-short return of -30.56% versus the benchmark S&P 500 of -15.64%.

Another example can be used to describe the small return earned in year 2010. The long portfolio is offsetting the loss of the short portfolio; for instance, the long portfolio delivered a return of 5.14% and the short portfolio 3.11%, leading to a small positive return for our long-short strategy of 2.03% versus the market delivering a return of 5.01% on average over 12 months. (Refer to Appendix A).

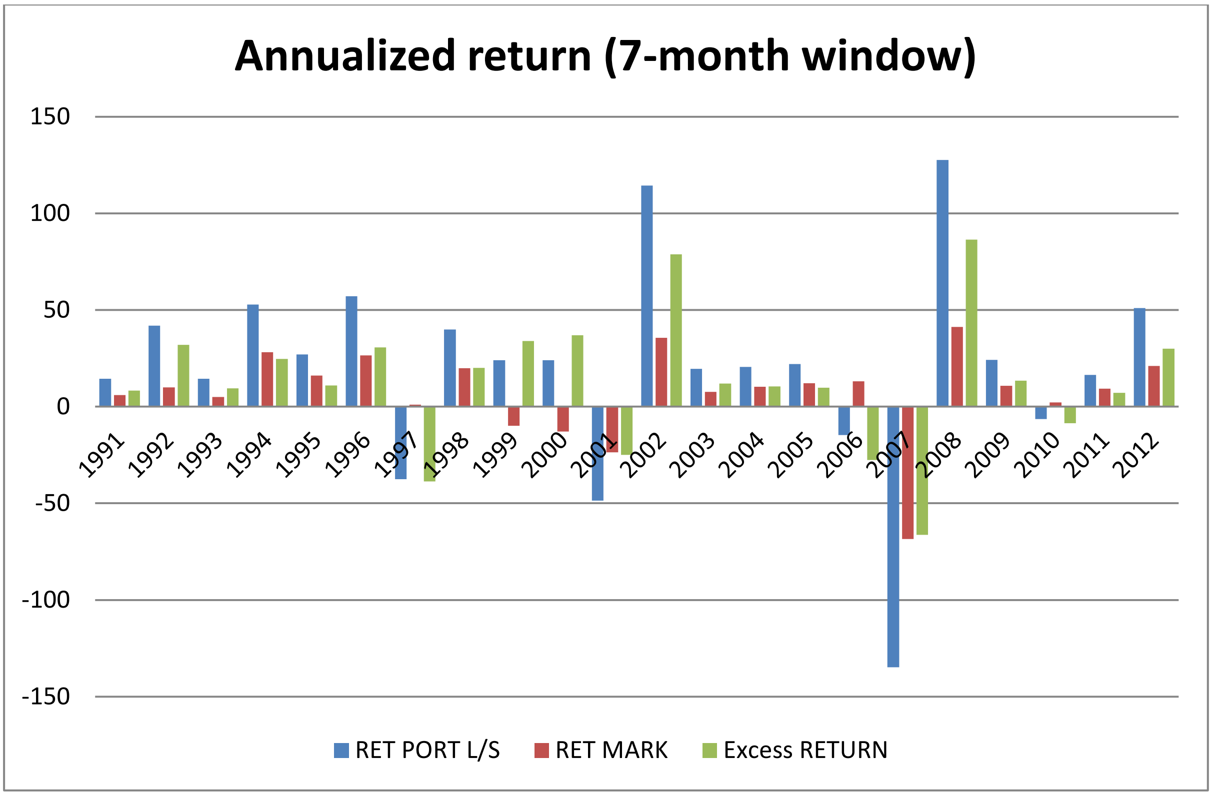

Figure 4.6-5 Long-short portfolio versus the market across a 7-month window

In Figure 4.6-5, we display the long-short portfolio 7-month annualized performance in returns for each fiscal year over the period shown in the chart, i.e. from 1991 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark, which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for five periods out of twenty-two. In other words, this means that investors would have above a 77% chance that we will return money if they were investing in our strategy over a 7-month window.

From each down period the strategy long-short seems to react well as we recover from massive loss. The strategy performed particularly well in the crisis years of 2002, 2008 and 2011 with gains of +114.41%, 127.56% and 16.41% over these three years compared with 35.60%, 41.20% and 9.31% respectively for the benchmark S&P 1500. In 2012 when looking at the 7-month annualized return the strategy long-short has outperformed with 50.96%, compared with 21.03% for the benchmark S&P 1500. The excess return earned above the market is about 29.92% on average over seven months. (Refer to Appendix A).

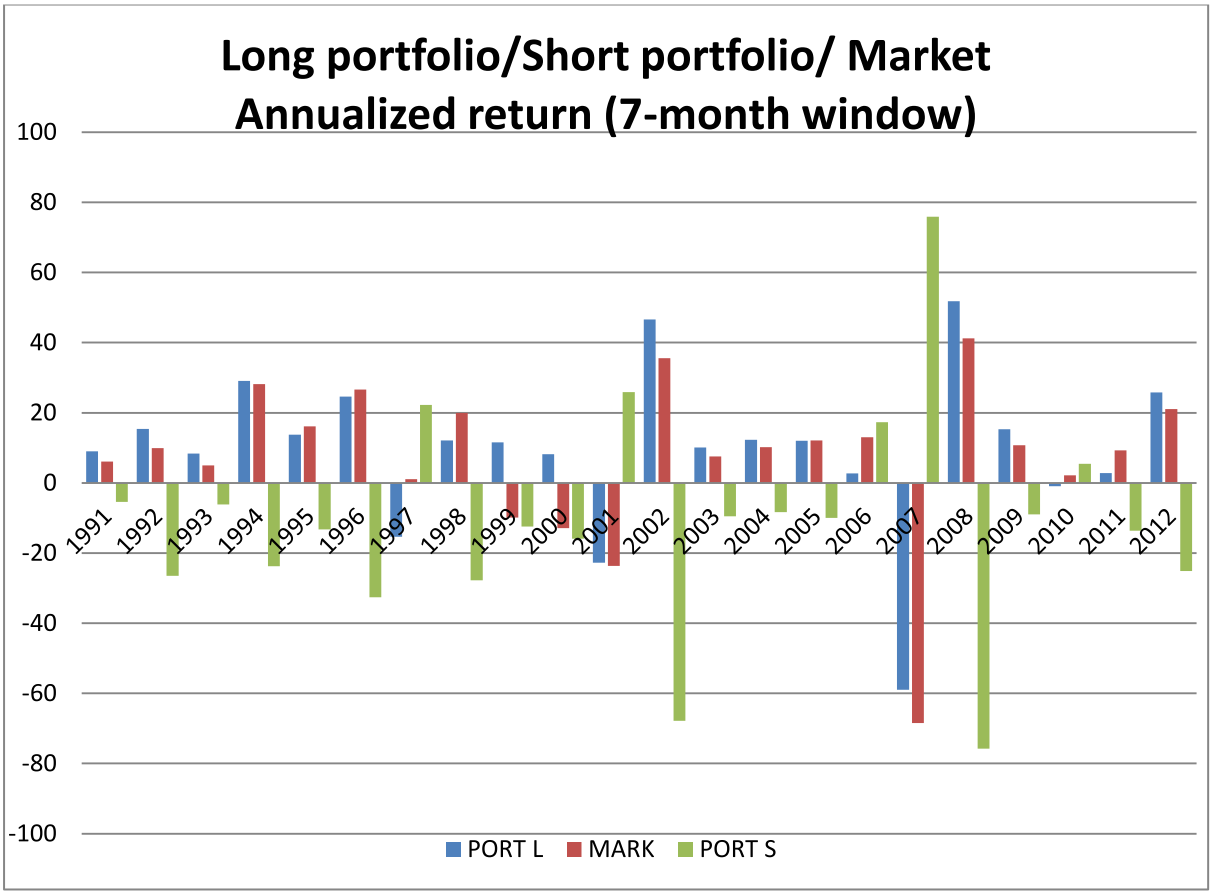

Figure 4.6-6 Details of the return that constitutes our long-short strategy (7-month window)

In Figure 4.6-6, we show graphically how each portfolio is doing over the benchmark S&P 1500 over a 7-month annualized window. The idea is to highlight years where perhaps we could have increased weights in one of the two portfolios, long or short.

In 1993 the long portfolio has generated 8.36% and the short portfolio -6.15% versus 4.99% for the benchmark S&P 1500. This results overall in an excess return of 9.51%. The same can be described for the year 2001 where the long portfolio is underperforming as well as the short portfolio. During that year the long portfolio has returned -22.72% whilst the short portfolio has returned +25.89%, leading to a long-short return of -48.61% versus the benchmark S&P 500 of -23.69%.

Another example can be used to describe the small loss earned in year 2010. Compared to a 12-month annualized window where the year 2010 was still positive, on a 7 month-window we were not able to return a positive return to the investor. For instance, the long portfolio delivered a return of -0.91% and the short portfolio +5.42%, leading to a small negative return for our long-short strategy of -6.33% versus the market delivering a return of 2.16% on average over three months. (Refer to Appendix A).

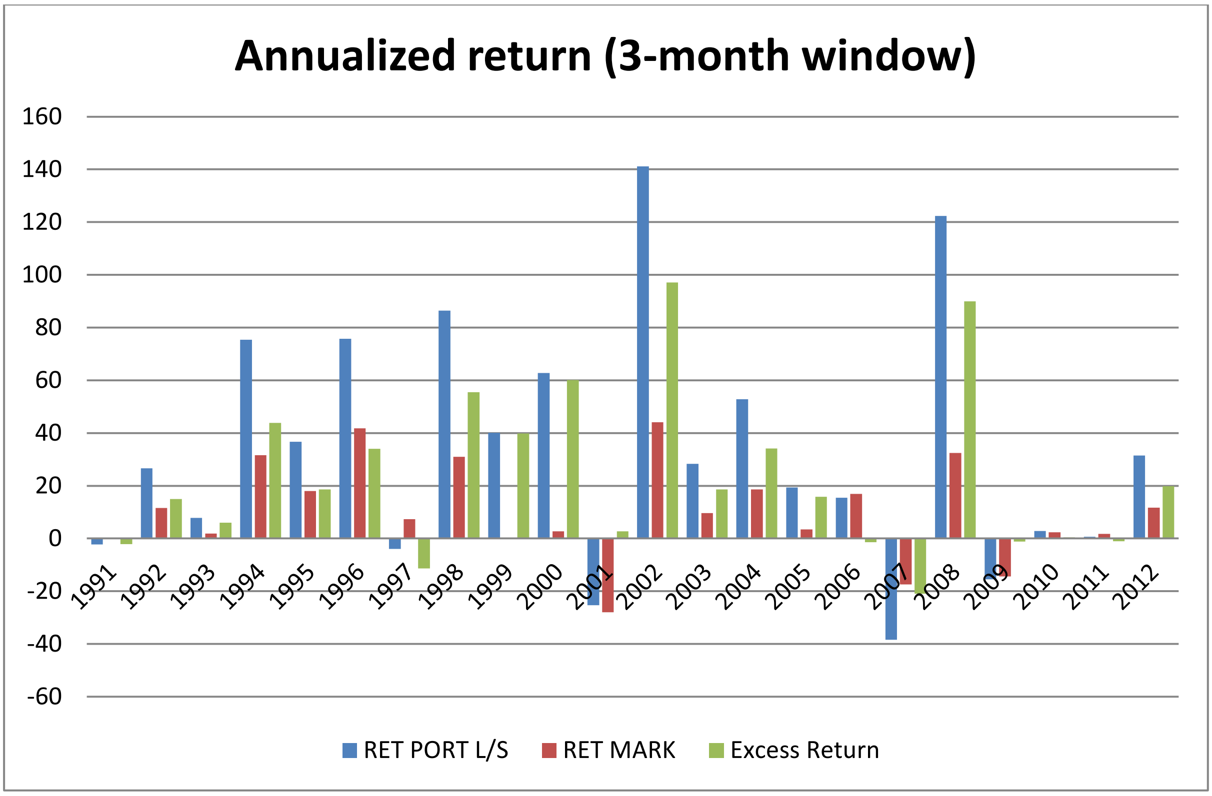

Figure 4.6-7 Long-short portfolio versus the market across a 3-month window

In Figure 4.6-7, we display the long-short portfolio 3-month annualized performance in returns for each fiscal year over the period shown in the chart, i.e. from 1991 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark, which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for six periods out of twenty-two. In other words, this means that investors would have above a 72% chance that we will return money if they were investing in our strategy over a 3-month window.

From each down period the strategy long-short seems to react well as we recover from massive loss.

Previously, our results showed years that were recovering from previous loss using a 12-month and a 7-month window – especially in the crisis years of 2002, 2008 and 2011. However, this pattern was not true in 2011 for our 3-month window, perhaps because we have not left enough time for stocks to increase their value.

The strategy performed particularly well in the crisis years of 2002 and 2008 with gains of 141.21% and 122.32% over these two years compared with 44.04% and 32.38% respectively for the benchmark S&P 1500. In 2012 when looking at the 3-month annualized return the strategy long-short has outperformed with 31.53%; this is the lowest return earned among the three period windows even if still significant, compared with 11.72% for the benchmark S&P 1500. The excess return earned above the market is about 19.81%. (Refer to Appendix A).

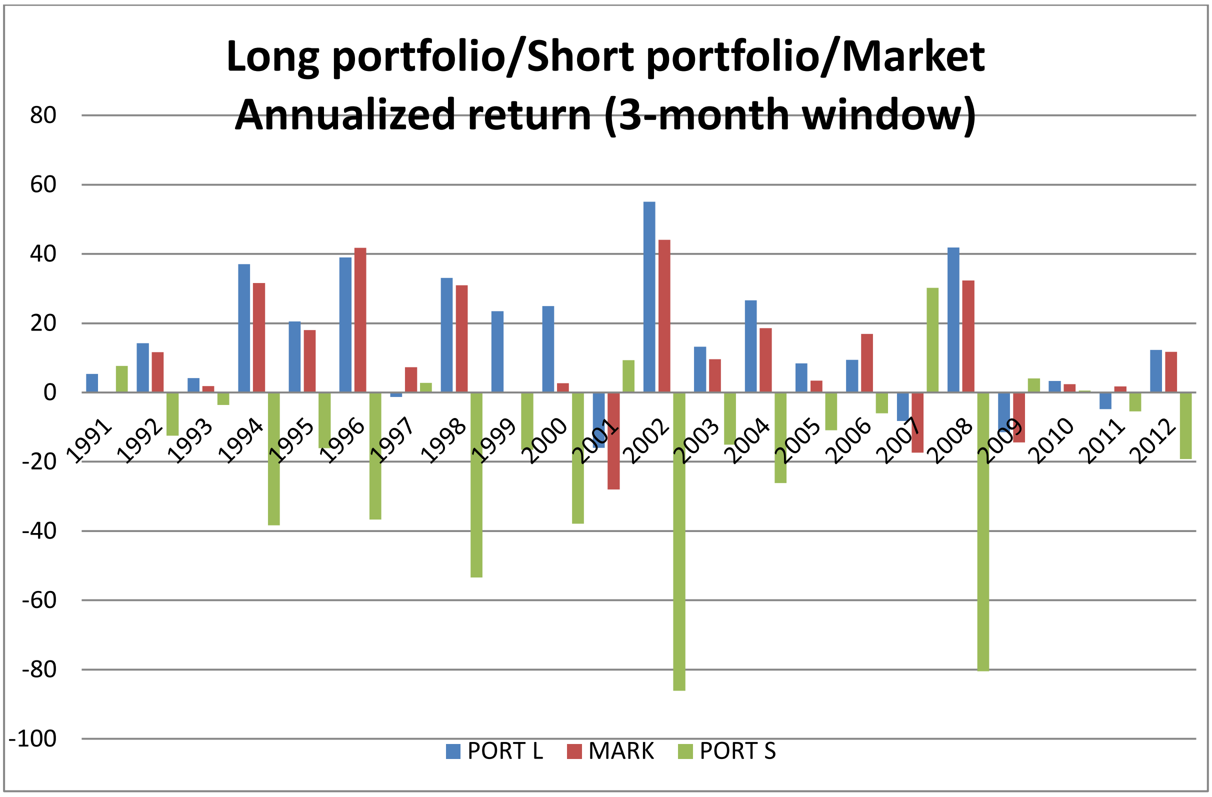

Figure 4.6-8 Details of the return that constitutes our long-short strategy (3-month window)

In Figure 4.6-8, we show graphically how each portfolios is doing over the benchmark S&P 1500 over a 3-month annualized window. The idea is to highlight years where perhaps we could have increased weights in one of the two portfolios long or short.

In 1993 the long portfolio has generated 4.19 and the short portfolio -3.57% versus 1.84% for the benchmark S&P 1500. This results overall in an excess return of 5.93%. The same can be described for the year 2001 where the long portfolio is underperforming as well as the short portfolio. During that year the long portfolio has returned -16.01% whilst the short portfolio has returned +9.34%, leading to a long-short return of -25.34% versus the benchmark S&P 500 of -28.00%. In that case, the three months' time window benefits our investors as this is the lowest loss over the three different periods.

Previously, the strategy in 2010 over a 7-month window was returning a negative return compared to the 12-month window. Here, the return earned on the long-short portfolio is slightly greater than the one on the 12-month window. For instance, the long portfolio delivered a return of +3.35% and the short portfolio +0.51%, leading to a small positive return for our long-short strategy of 2.83% versus the market delivering a return of 2.37%. (Refer to Appendix A).

4.6.2 Drawdown

In this part, we present the maximum drawdown over the different time horizons.

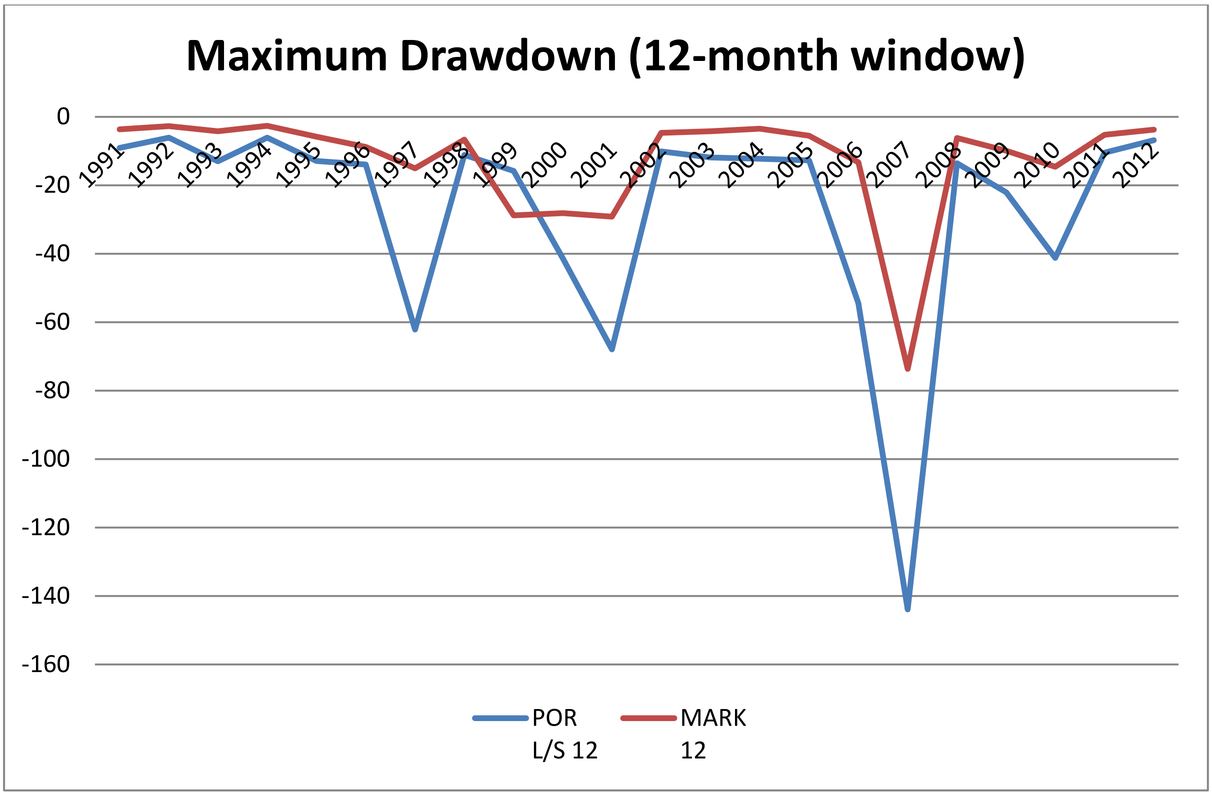

Figure 4.6-9 Maximum drawdown (12-month window)

In Figure 4.6-9, we present the maximum drawdown of our strategy over a 12-month horizon window for the period 1991 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -143.94% in 2007 compared to -73.67% for the benchmark; here the S&P 1500 is identified in the chart by “MARK 12”. The second largest drawdown of our strategy occurs in 2001 with a drawdown of -67.94% compared to the benchmark of -29.18% the same year. The third largest drawdown is in 1997, -62.11% compared to -15.04% respectively for the benchmark.

Historically, long-short equity portfolios have to some extent limited the downside risk during downwards markets. Our main concern is therefore why the maximum drawdown is somehow showing a more risky strategy for our long-short portfolio compared to the S&P 1500 index used as a benchmark here. (Refer to Appendix B).

One way to justify this is by highlighting that we have inside our portfolio a two-dimensional bet and, as spotted by the literature, this is not a pure market neutral play as we are looking for return on the long portfolio and the short portfolio, thereby justifying the higher drawdown of our strategy. Those maximum losses appear to be during pre-crisis times where our portfolio is losing on both sides of the two-dimensional bet. In summary, due to the absolute return investment approach, also called a double alpha strategy by practitioners, our portfolio exhibits higher risk compensated by significant return expectations for our investors.

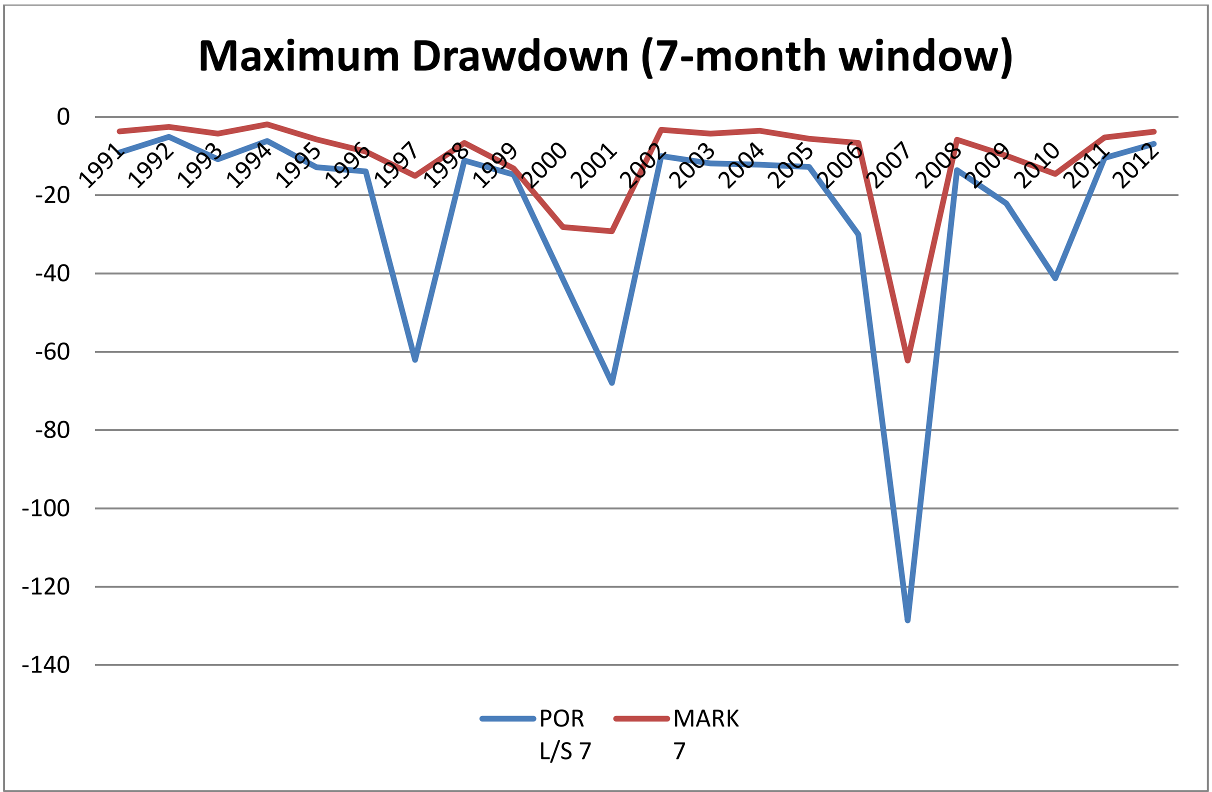

Figure 4.6-10 Maximum drawdown (7-month window)

In Figure 4.6-10, we present the maximum drawdown of our strategy over a 7-month horizon window for the period 1991 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -128.59% in 2007 compared to -62.27% for the benchmark; here the S&P 1500 is identified in the chart by “MARK 7”. The second largest drawdown of our strategy occurs in 2001 with a drawdown of -67.94% compared to the benchmark of -29.18% the same year. The third largest drawdown is in 1997 -62.11% compared to -15.04% respectively for the benchmark. (Refer to Appendix B).

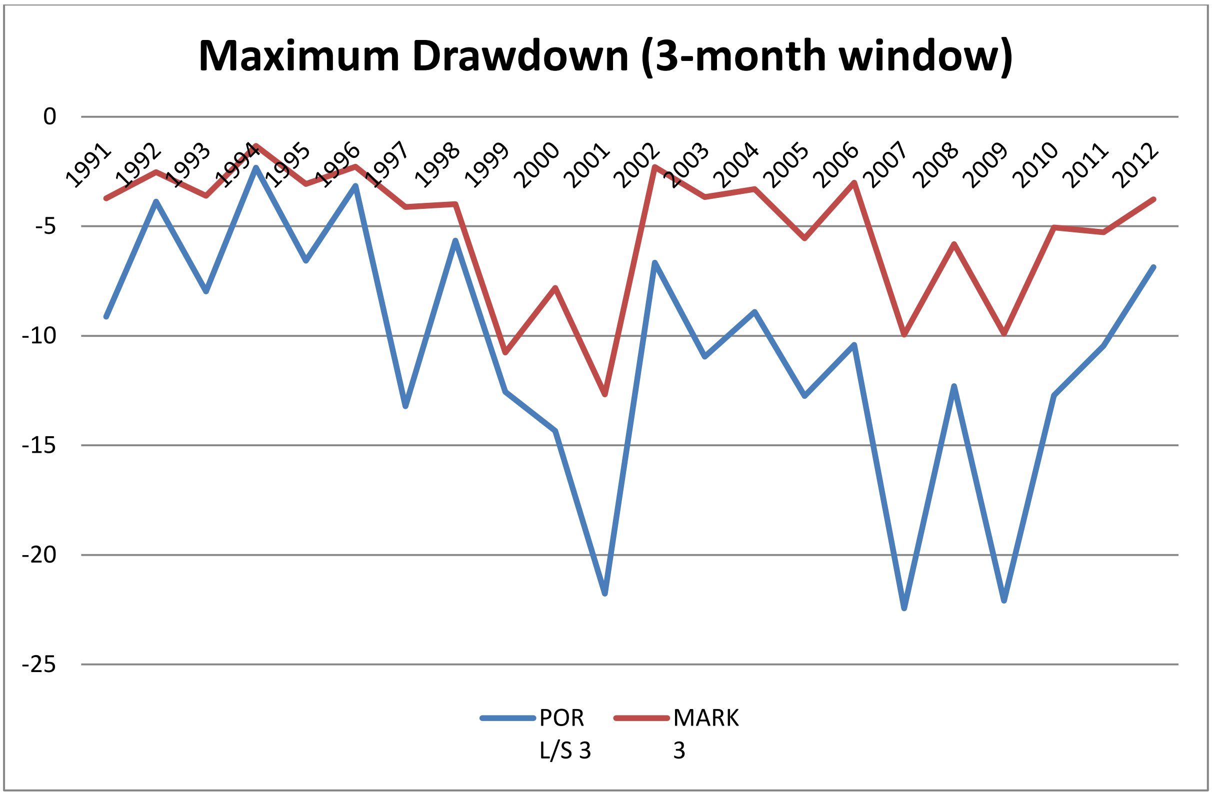

Figure 4.6-11 Maximum drawdown (3-month window)

In Figure 4.6-11, we present the maximum drawdown of our strategy over a 3-month horizon window for the period 1991 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -22.43% in 2007 compared to -9.94% for the benchmark; here the S&P 1500 is identified in the chart by "MARK 3". The second largest drawdown of our strategy occurs in 2001 with a drawdown of -21.77% compared to the benchmark of -12.68% the same year. The third largest drawdown is in 2000, -14.33% compared to -7.81% respectively for the benchmark.

To some extent as the maximum drawdown occurs gradually we would have been able to leave the strategy at this point in time in order to limit the downside risk. (Refer to Appendix B).

4.6.3 Beta

In this part, we describe beta over the different time horizons.

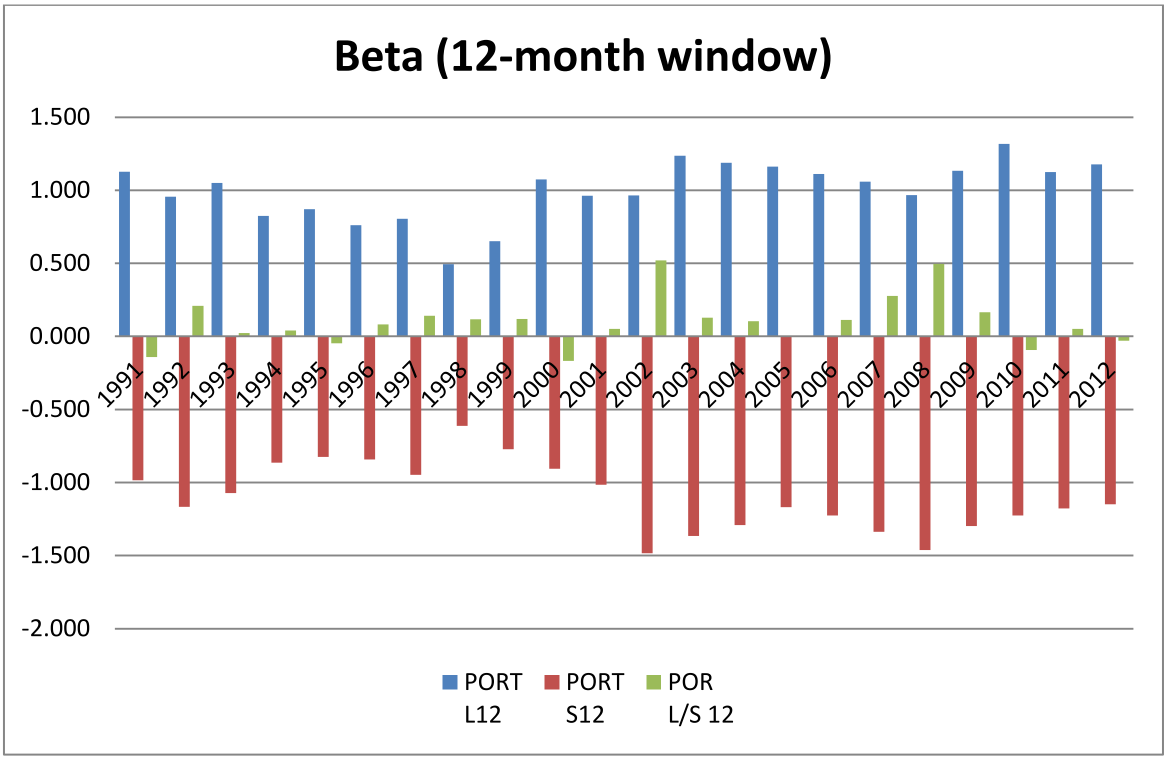

Figure 4.6-12 Beta (12-month window)

We present above in Figure 4.6-12 beta computed for a 12-month horizon window for three portfolios, i.e. the long portfolio denoted in "blue", the short portfolio in "red" and our long-short portfolio in "green".

By definition beta is the measurement of volatility of a portfolio in relation to the market. A portfolio with a beta of one will tend to move in line with the market; by contrast, a portfolio with a beta higher than one will be more volatile; inversely, a portfolio with a beta of less than one will be less volatile than the market.

A market neutral strategy will tend to have a beta close to zero; hence this symmetrical beta for the long and short portfolio. For example, in 2010 the beta on the long portfolio of 1.32 shows that the portfolio has performed 32% better than the benchmark, here the S&P 1500. The reverse if the market is falling.

Also, in 2010 the beta on the short portfolio of -1.23 shows that the short portfolio has performed 23% better than the benchmark on the downside. Inversely, in 1997 the beta on the long portfolio of 0.81 shows that the portfolio is expected to perform 19% worse than the market during up markets and 19% better during down markets.

Regarding our long-short portfolio we are adding on both betas, such as in 2010, for example, the portfolio has a beta of -0.09.

Long-short equity portfolio managers are looking to increase their alpha and this is expressed by higher return above the market; the other way is to decrease your beta. (Refer to Appendix C).

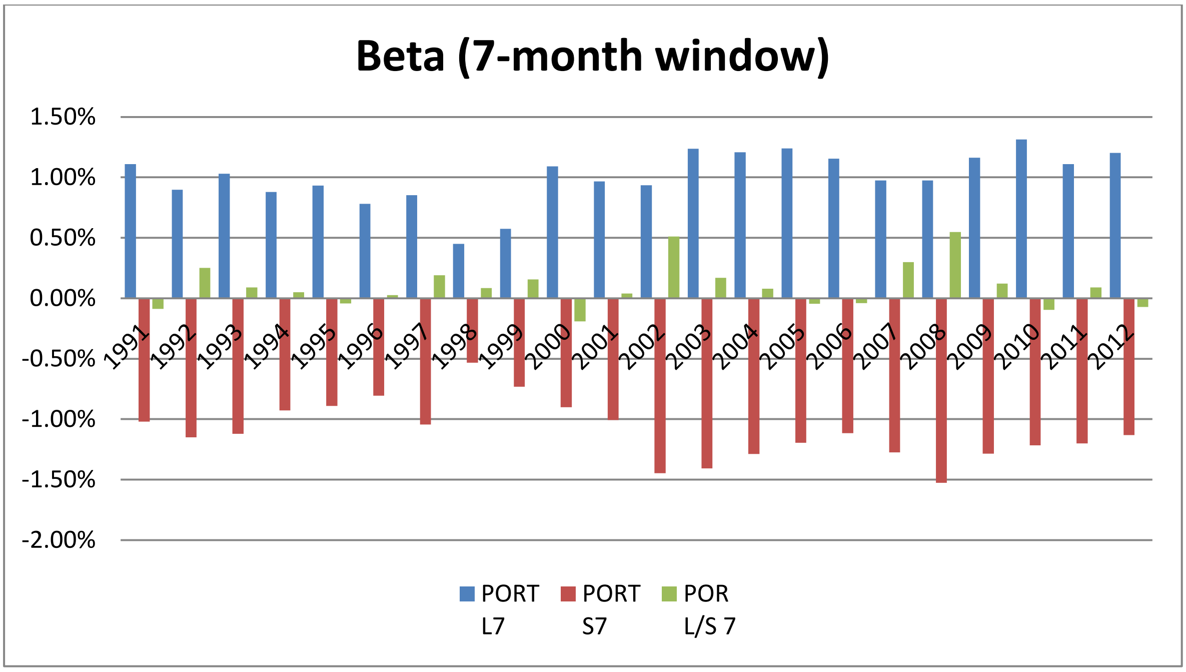

Figure 4.6-13 Beta (7-month window)

In Figure 4.6-13, we illustrate the beta for a 7-month horizon window for three portfolios, i.e. the long portfolio denoted in “blue”, the short portfolio in “red” and our long-short portfolio in “green”.

For example, in 2010 the beta on the long portfolio of 1.31 shows that the portfolio has performed 31% better than the benchmark, here the S&P 1500. The reverse if the market is falling.

Also, in 2010 the beta on the short portfolio of -1.22 shows that the short portfolio has performed 22% better than the benchmark on the downside. Inversely, in 1997 the beta on the long portfolio of 0.85 shows that the portfolio is expected to perform 15% worse than the market during up markets and 15% better during down markets. (Refer to Appendix C.)

Regarding our long-short portfolio we are adding on both betas, such as in 2010, for example, the portfolio has a beta of -0.10. Long-short equity portfolio managers are looking to increase their alpha and this is expressed by higher return above the market; the other way is to decrease your beta.

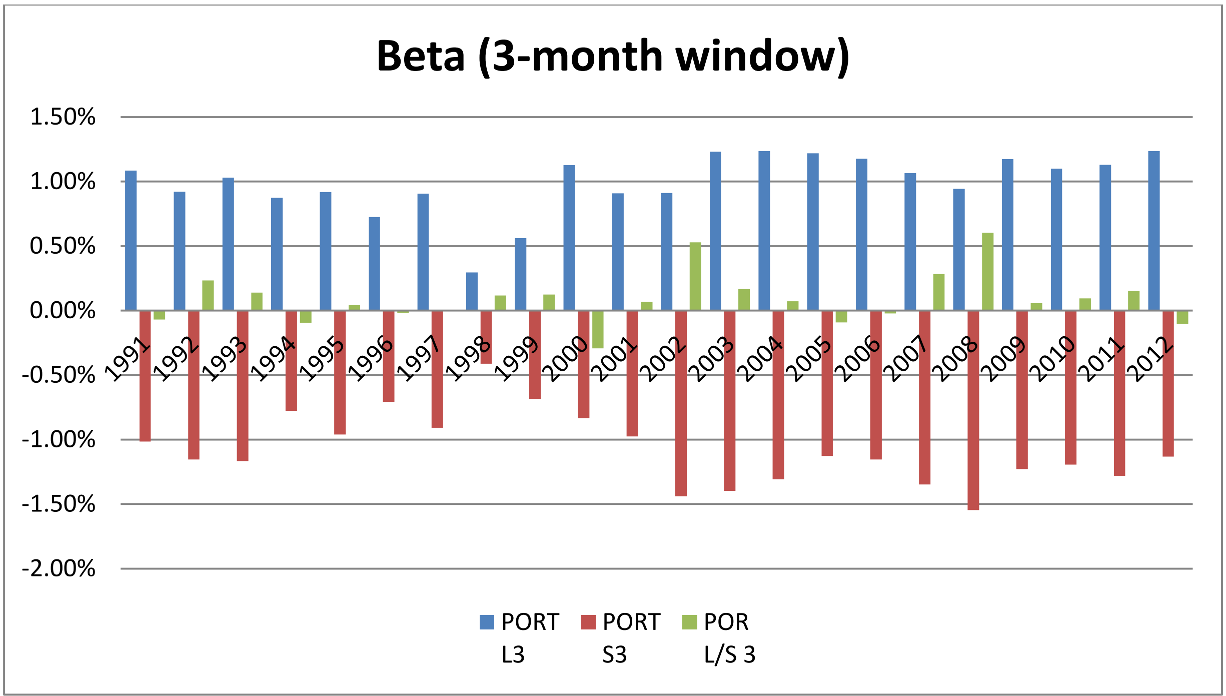

Figure 4.6-14 Beta (3-month window)

In Figure 4.6-14, we illustrate the beta for a 3-month horizon window for three portfolios, i.e. the long portfolio denoted in "blue", the short portfolio in "red" and our long-short portfolio in "green".

For example, in 2010 the beta on the long portfolio of 1.10 shows that the portfolio has performed 10% better than the benchmark, here the S&P 1500. The reverse if the market is falling.

Also, in 2010 the beta on the short portfolio of -1.19 shows that the short portfolio has performed 19% better than the benchmark on the downside. Inversely, in 1997 the beta on the long portfolio of 0.91 shows that the portfolio is expected to perform 9% worse than the market during up markets and 9% better during down markets.

Regarding our long-short portfolio we are adding on both betas, such as in 2010, for example, the portfolio has a beta of -0.09. (Refer to Appendix C.)

Long-short equity portfolio managers are looking to increase their alpha and this is expressed by higher return above the market; the other way is to decrease beta. (Refer to Appendix D.)

4.6.4 Sharpe ratio/Information ratio/Sortino ratio/Treynor ratio

In this part, we analyze the different ratios over the different time horizons.

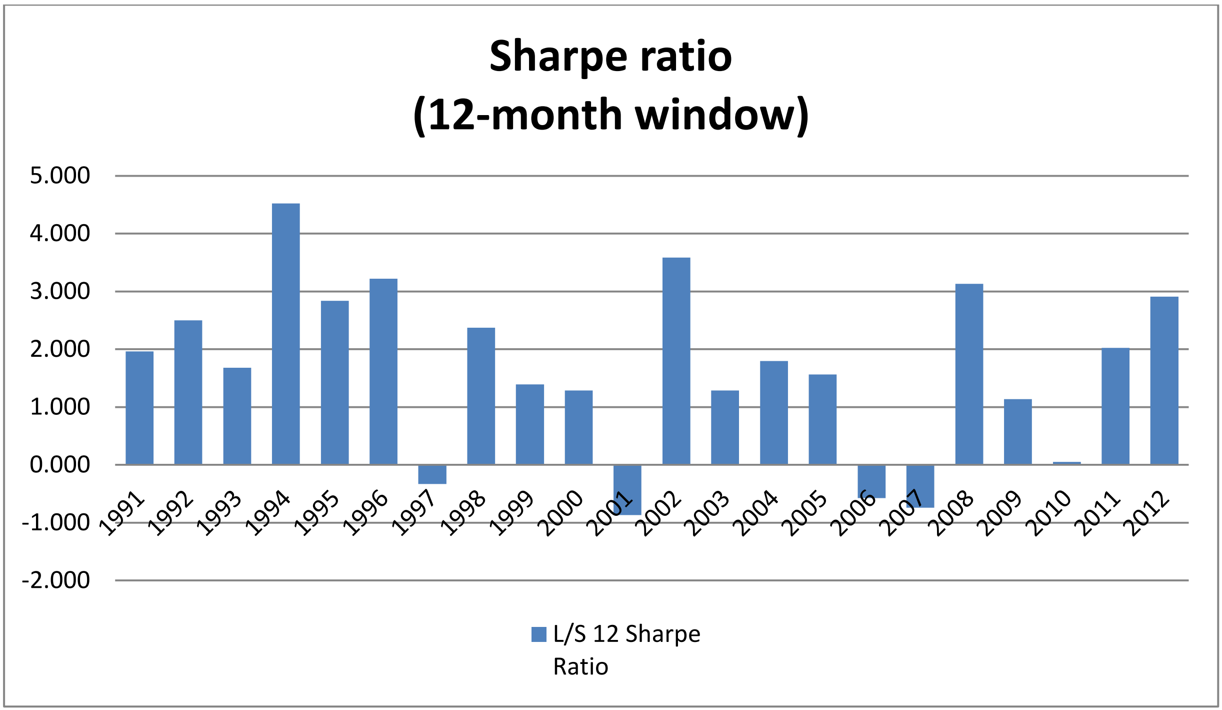

Figure 4.6-15 Sharpe ratio (12-month window)

In Figure 4.6-15, the Sharpe ratio is used to express how much return is achieved for the amount of risk taken in an investment; when interpreting Sharpe ratios investors look at the highest one, as the higher the ratio the better the fund.

As an illustration, the above chart shows the Sharpe ratios calculated for our long-short portfolio over the different years on a 12-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 2.906% per annum per unit of volatility, which corresponds to a Sharpe ratio of 2.906; by contrast, a Sharpe ratio below 1 as identified in 2010 (0.049) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional to the risk taken as, for example, in 2009 (1.133). In this chart the Sharpe ratio ranges from -0.868 in 2001 to 4.522 in 1994. The mean and the median are both around 1.6. (Refer to Appendix D.)

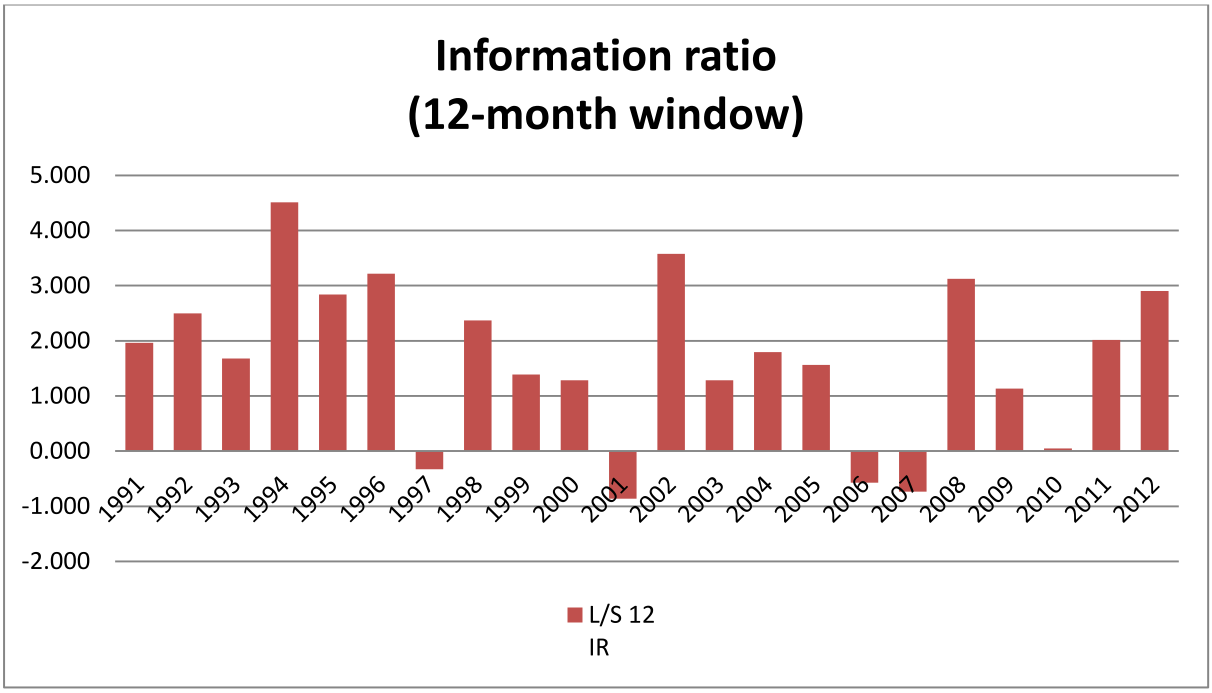

Figure 4.6-16 Information ratio (12-month window)

In Figure 4.6-16, the Information ratio is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using the same investment style the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -0.736, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -0.864 in 2001 to 4.514 in 1994. The mean and the median are both around 1.6. (Refer to Appendix D.)

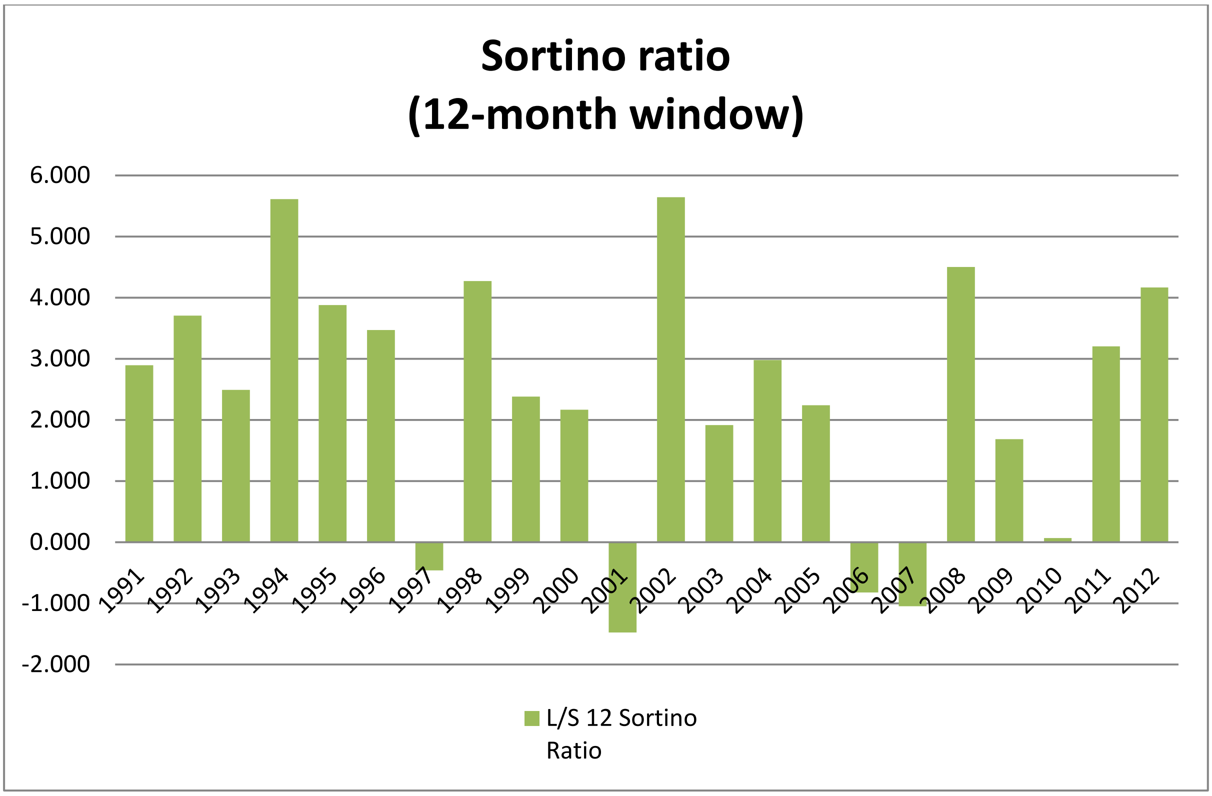

Figure 4.6-17 Sortino ratio (12-month window)

In Figure 4.6-17, the Sortino ratio which replaces the volatility in the Sharpe ratio with a measure of downside deviations confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -1.479 in 2001 to 5.642 in 2002. The mean and the median are both around 2.5. (Refer to Appendix D.)

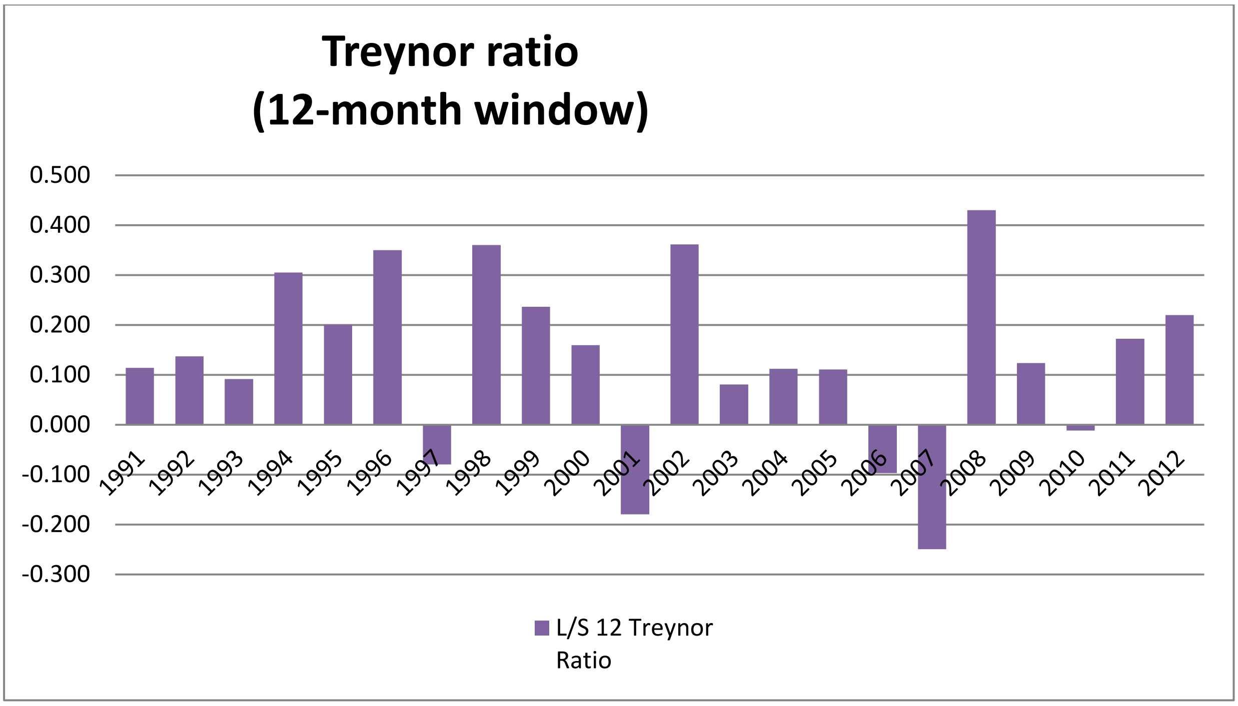

Figure 4.6-18 Treynor ratio (12-month window)

In Figure 4.6-18, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar return. In this chart, the Treynor ratio ranges from -0.250 in 2007 to 0.430 in 2008. The mean and the median are both around 0.130. (Refer to Appendix D.)

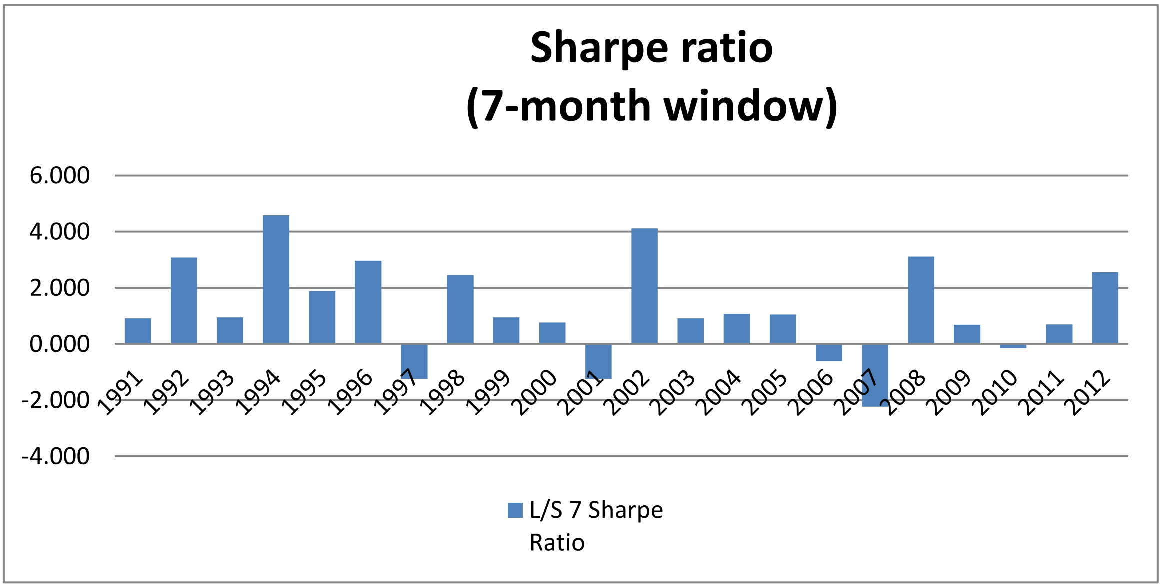

Figure 4.6-19 Sharpe ratio (7-month window)

In Figure 4.6-19, we present the Sharpe ratios calculated for our long-short portfolio over the different years on a 7-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 2.556% per annum per unit of volatility, which corresponds to a Sharpe ratio of 2.556; by contrast, a Sharpe ratio below 1 as identified in 1999 (0.945) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional to the risk taken as, for example, in 2005 (1.045). In this chart, the Sharpe ratio ranges from -2.234 in 2007 to 4.588 in 1994. The mean and the median are both around 1. (Refer to Appendix D.)

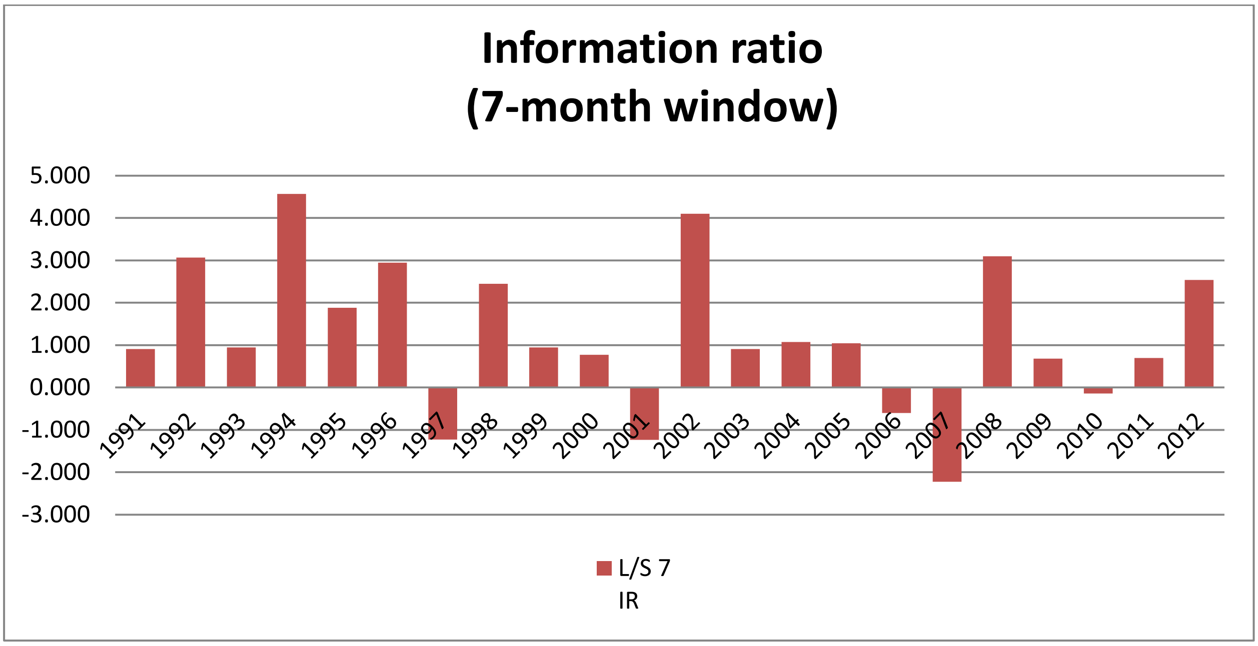

Figure 4.6-20 Information ratio (7-month window)

In Figure 4.6-20, the Information ratio is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using the same investment style the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -2.223, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -2.223 in 2007 to 4.570 in 1994. The mean and the median are both around 1. (Refer to Appendix D.)

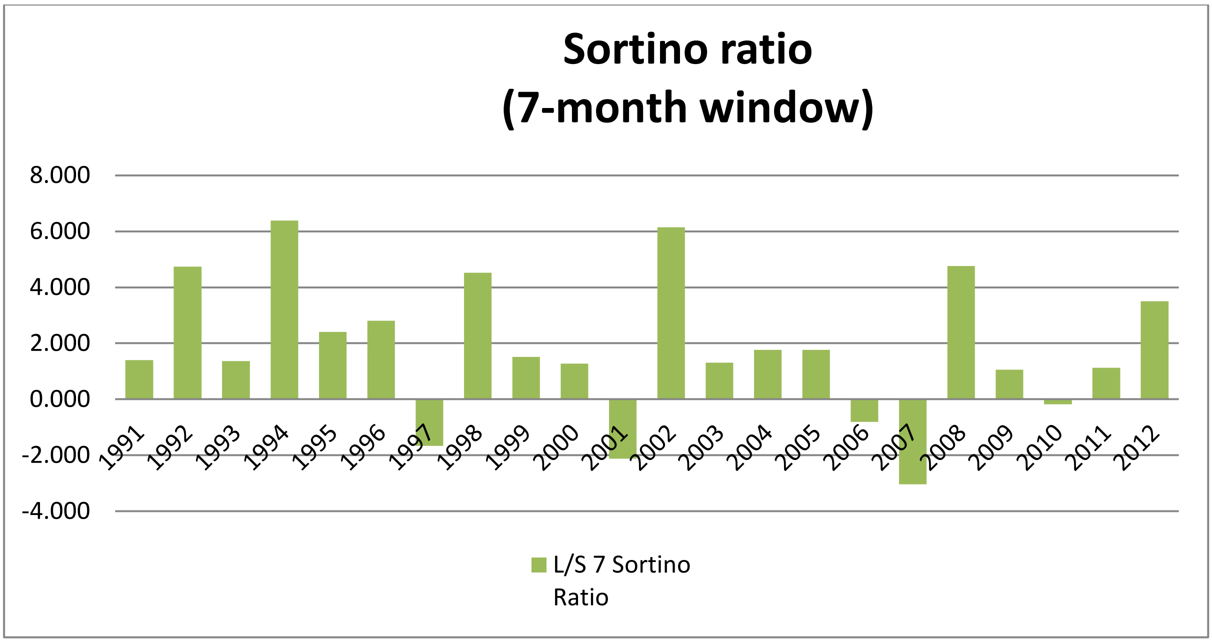

Figure 4.6-21 Sortino ratio (7-month window)

In Figure 4.6-21, the Sortino ratio which replaces the volatility in the Sharpe ratio with a measure of downside deviations confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -3.041 in 2007 to 6.382 in 1994. The mean and the median are both around 1.5. (Refer to Appendix D.)

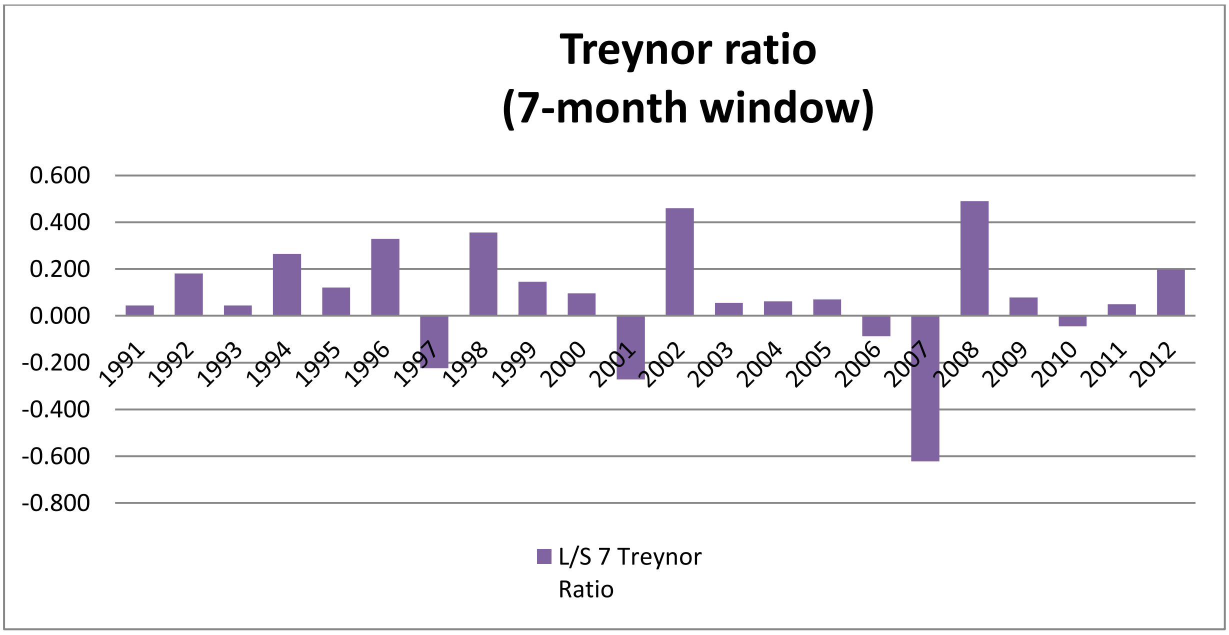

Figure 4.6-22 Treynor ratio (7-month window)

In Figure 4.6-22, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar returns. In this chart, the Treynor ratio ranges from -0.622 in 2007 to 0.490 in 2008. The mean and the median are both around 0.080. (Refer to Appendix D.)

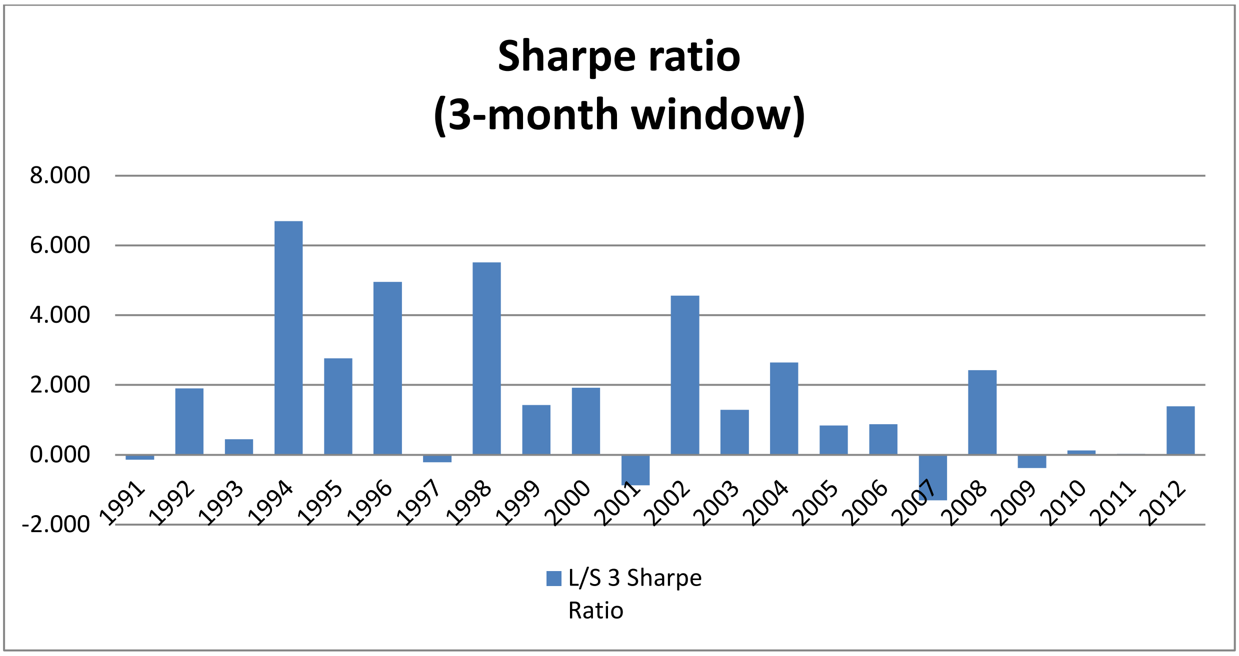

Figure 4.6-23 Sharpe ratio (3-month window)

In Figure 4.6-23, we present the Sharpe ratios calculated for our long-short portfolio over the different years on a 3-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 1.388% per annum per unit of volatility, which corresponds to a Sharpe ratio of 1.388; by contrast, a Sharpe ratio below 1 as identified in 2010 (0.127) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional for the risk taken as, for example, in 2003 (1.286). In this chart, the Sharpe ratio ranges from -1.304 in 2007 to 6.696 in 1994. The mean and the median are both around 1.4. (Refer to Appendix D.)

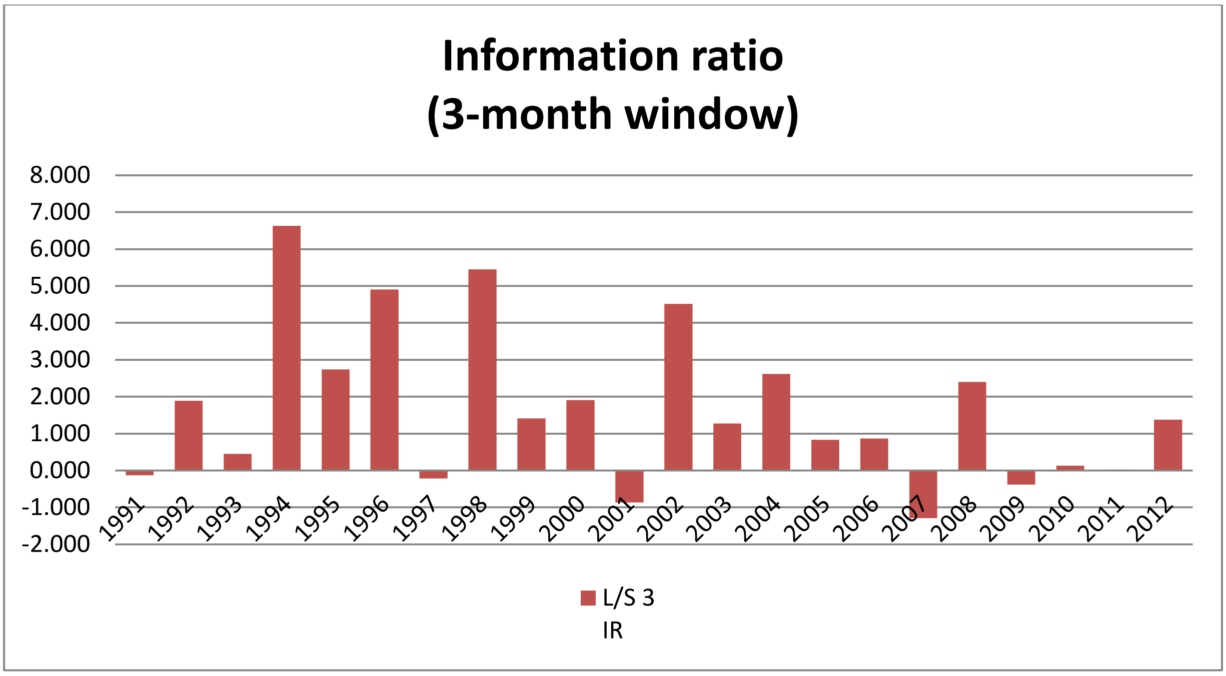

Figure 4.6-24 Information ratio (3-month window)

In Figure 4.6-24, the Information ratio is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using the same investment style the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -1.288, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -1.288 in 2007 to 6.627 in 1994. The mean and the median are both around 1.4. (Refer to Appendix D.)

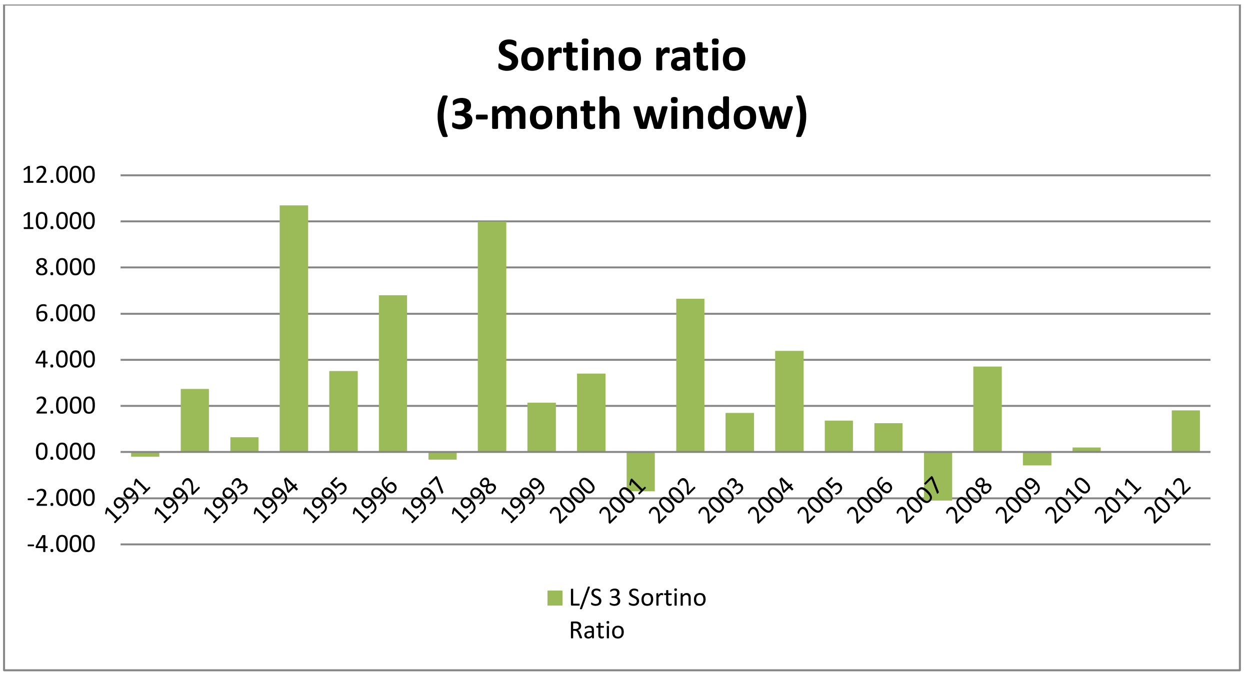

Figure 4.6-25 Sortino ratio (3-month window)

In Figure 4.6-25, the Sortino ratio, which replaces the volatility in the Sharpe ratio with a measure of downside deviations, confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -2.098 in 2007 to 10.687 in 1994. The mean and the median are both around 2. (Refer to Appendix D.)

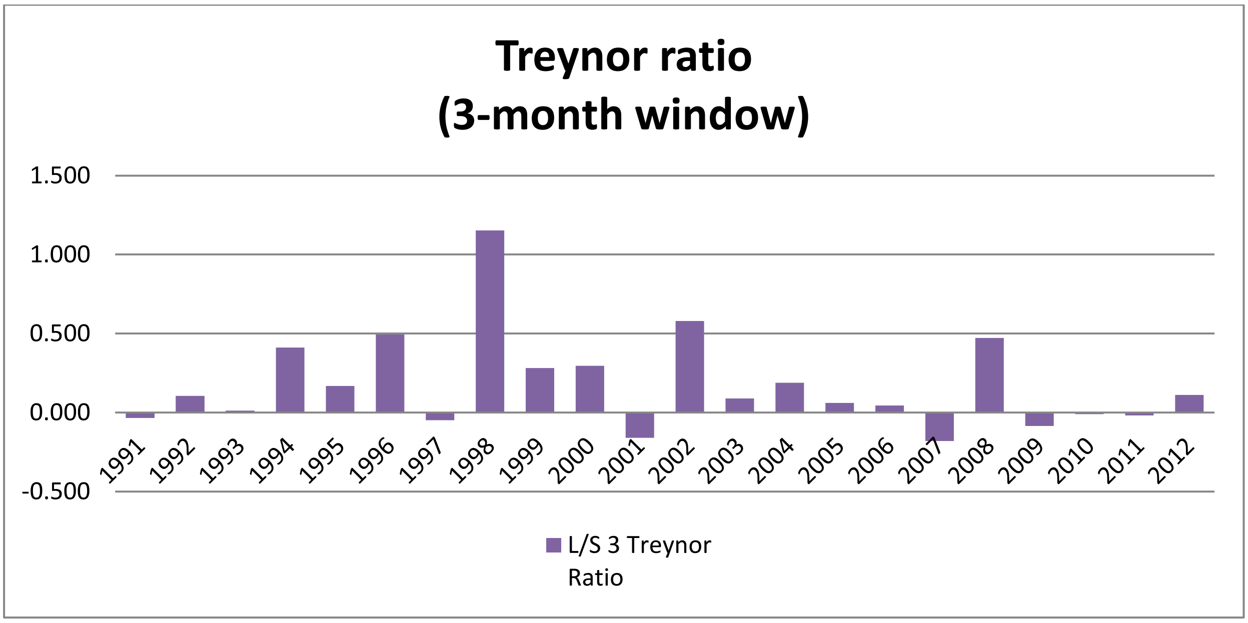

Figure 4.6-26 Treynor ratio (3-month window)

Finally, in Figure 4.6-26, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar returns. In this chart, the Treynor ratio ranges from -0.180 in 2007 to 1.154 in 1998. The mean and the median are both around 0.100. (Refer to Appendix D.)

4.6.5 Correlation

In this part, we present a chart and a summary results table obtained for the correlation of our portfolios, i.e. the long portfolio, the short portfolio and the long-short portfolio against the market.

Correlation is a useful metric when measuring how the returns of two investments move in relation to each other; we display below a chart on a 3-month window with the correlation for the long portfolio, the short portfolio and the long-short portfolio. The results display a symmetrical correlation for both long and short portfolio. The same can be observed on a 7-month or a 12-month window.

In general, long-short equity portfolios tend to have long bias and are in consequence less correlated with the market; this is reflected in our graph with the low correlation obtained for our long-short portfolio.

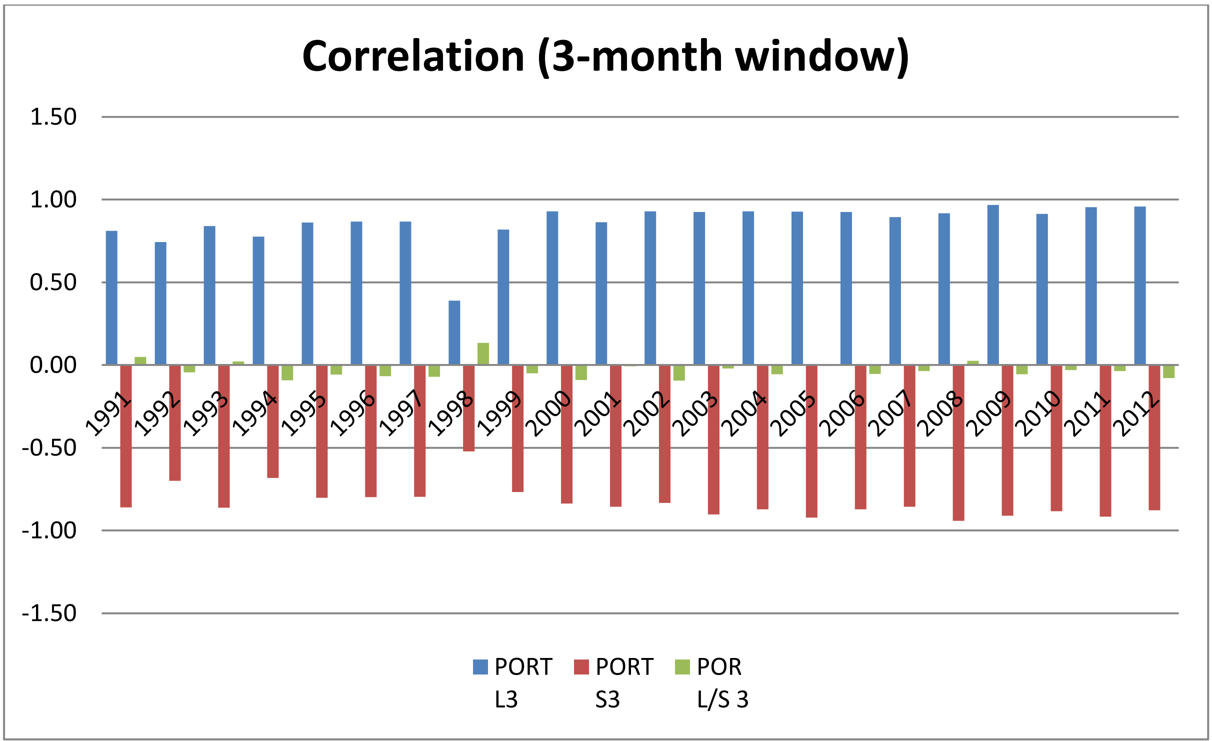

Figure 4.6-27 Correlation (3-month window)

In Figure 4.6-27, we display the correlation chart for our 3-month annualized window. It presents the correlations between our portfolios and the S&P 1500. The correlation overall is quite low with, for example, in 2012 the long portfolio exhibiting a positive correlation of 0.89 with the S&P 1500 whilst the short portfolio exhibits a negative correlation the same year of -0.76 with the S&P 1500. The correlation of our long-short portfolio is -0.08, indicating that the portfolio is neutral and offering diversification for investors willing to use our portfolio in a fund. (Refer to Appendix E.)

4.6.6 Volatility

We show in this part graphics representing the return on our long-short portfolio against the market and the volatility for both. This helps us to understand to what extent our strategy is more volatile by comparing returns for the risk taken. The results show that for not a much higher volatility our strategy is able to generate higher return than the market.

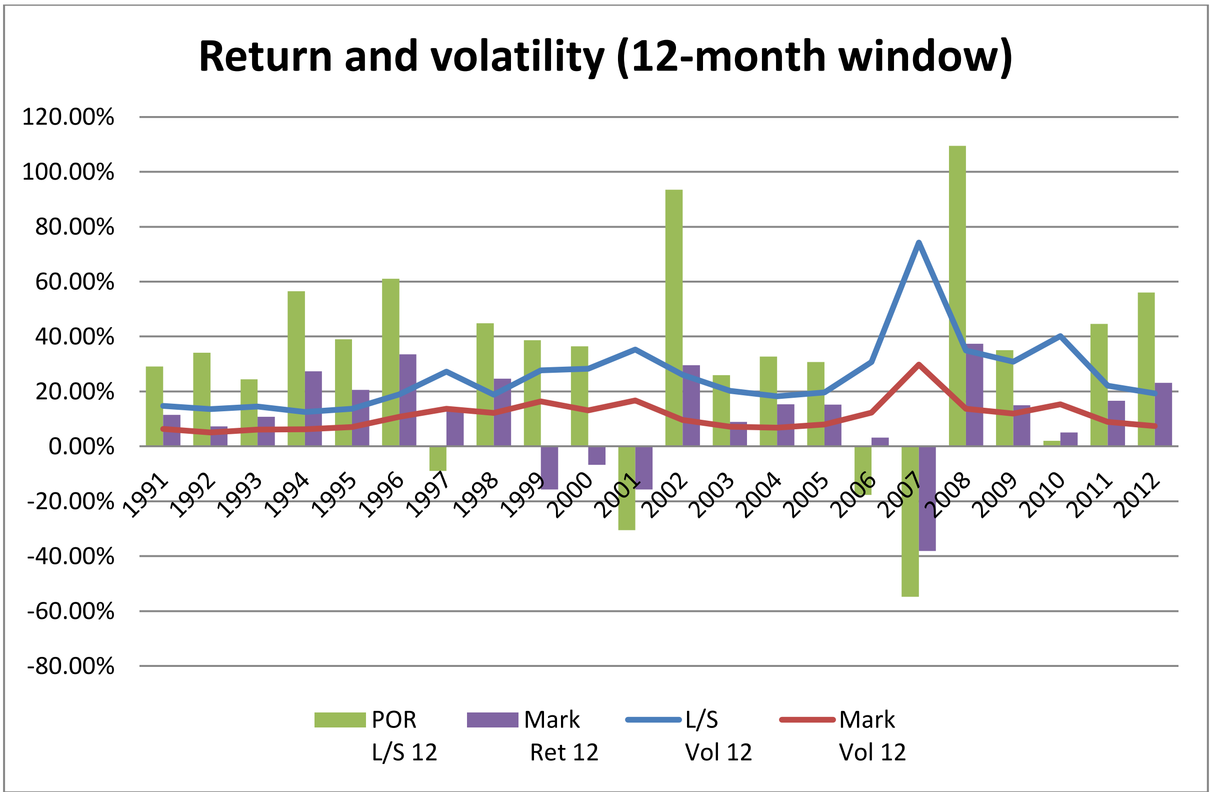

Figure 4.6-28 Return and volatility for long-short portfolio against market (12-month window)

In Figure 4.6-28, we present annualized returns and annualized volatility on a 12-month window horizon. The results show that for not a much greater volatility we are able to generate higher return. For illustration purposes, during periods of high market volatility investors are likely to see return to be negative, for instance in 2007, 2001 or 1997. It should also be noted that during those crisis times our portfolio is facing a double volatility on both sides of the portfolio, i.e. the long portfolio and the short portfolio. (Refer to Appendix F.)

As an example, in 2007 the portfolio has a negative return of -54.81% for a volatility of 74.25% whilst the market has a negative return of -38.11% for a volatility of 29.83%, meaning that our strategy relative to the market is not very risky even during crisis times.

In the following figure, 4.6-29, we represent a scatter diagram with, on the y-axis, the return of our long-short portfolio against the market and on the x-axis the volatility of our long-short portfolio against the volatility of the market on a 12-month annualized window.

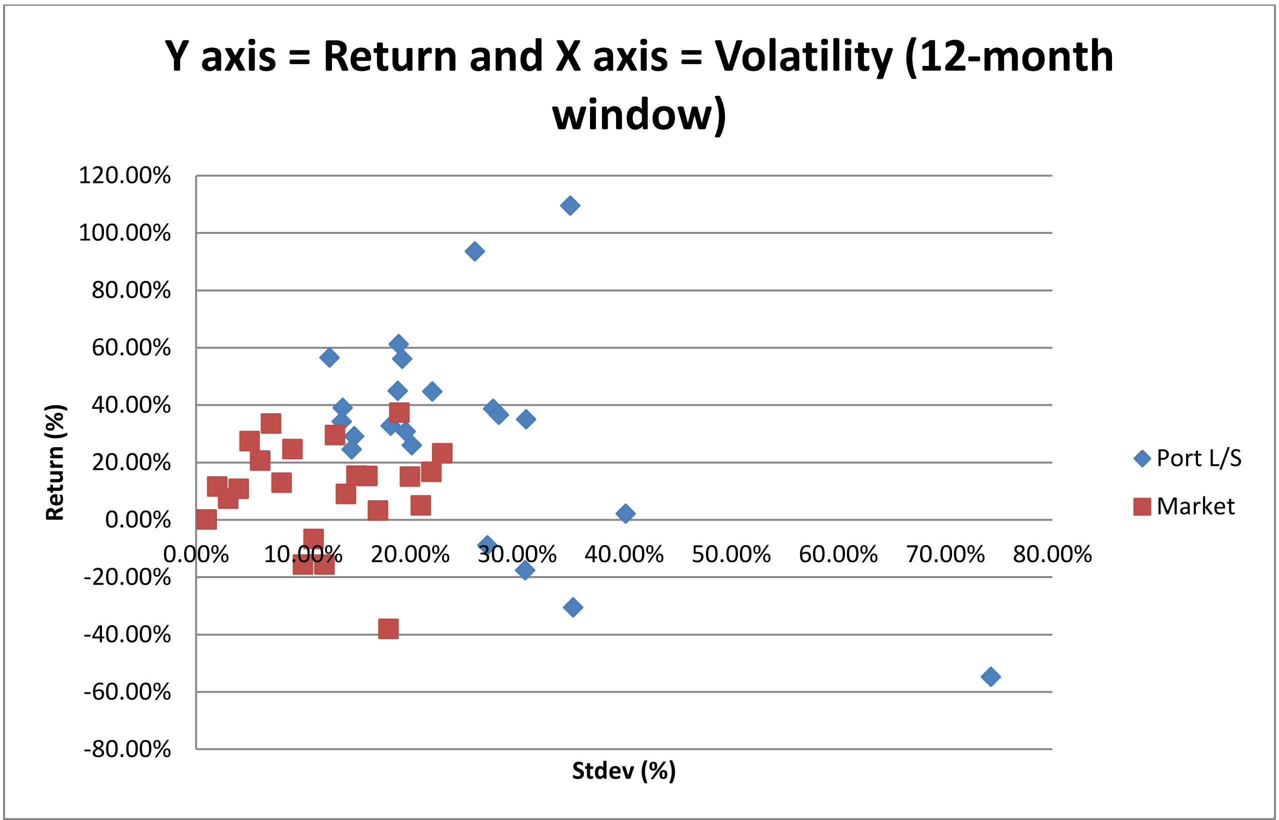

Figure 4.6-29 Scatter diagram return and volatility (12-month window)

Figure 4.6-29 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot, investors will be able to understand that for the same level of risk our strategy is delivering a higher return, as suggested by the concentration on around 20% standard deviation. (Refer to Appendix F.)

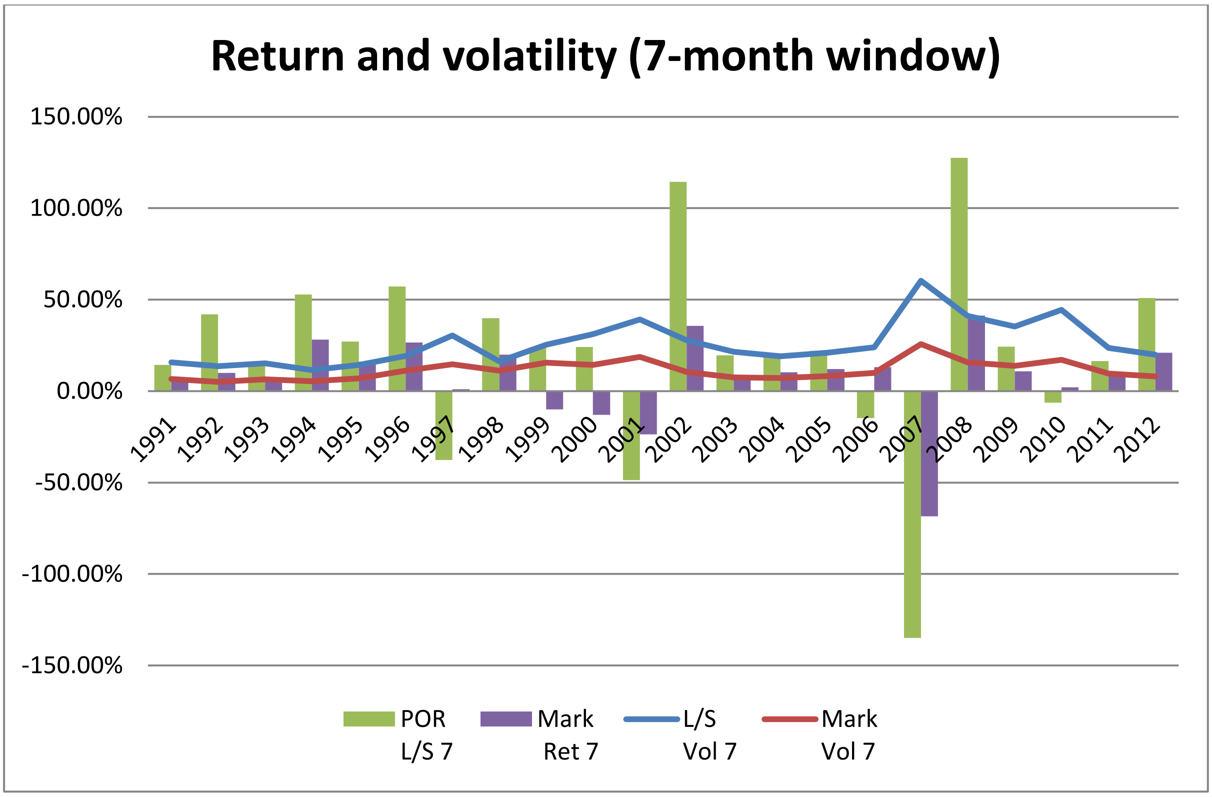

Figure 4.6-30 Return and volatility for long-short portfolio against market (7-month window)

In Figure 4.6-30, we present annualized returns and annualized volatility on a 7-month window horizon. The results are showing that for not a much greater volatility we are able to generate higher returns. For illustration purposes, during periods of high market volatility investors are likely to see returns to be negative, for instance in 2007, in 2001 or in 1997. It should also be noted that during those crisis times our portfolio is facing a double volatility on both sides of the portfolio, i.e. the long portfolio and the short portfolio.

As an example, in 2007 the portfolio has a negative return of -134.83% for a volatility of 60.37% whilst the market has a negative return of -68.48% for a volatility of 25.71%, meaning that our strategy relative to the market is not very risky even during crisis times.

In the following figure, 4.6-31, we represent a scatter diagram with, on the y-axis, the return of our long-short portfolio against the market and on the x-axis the volatility of our long-short portfolio against the volatility of the market on a 7-month annualized window. (Refer to Appendix F.)

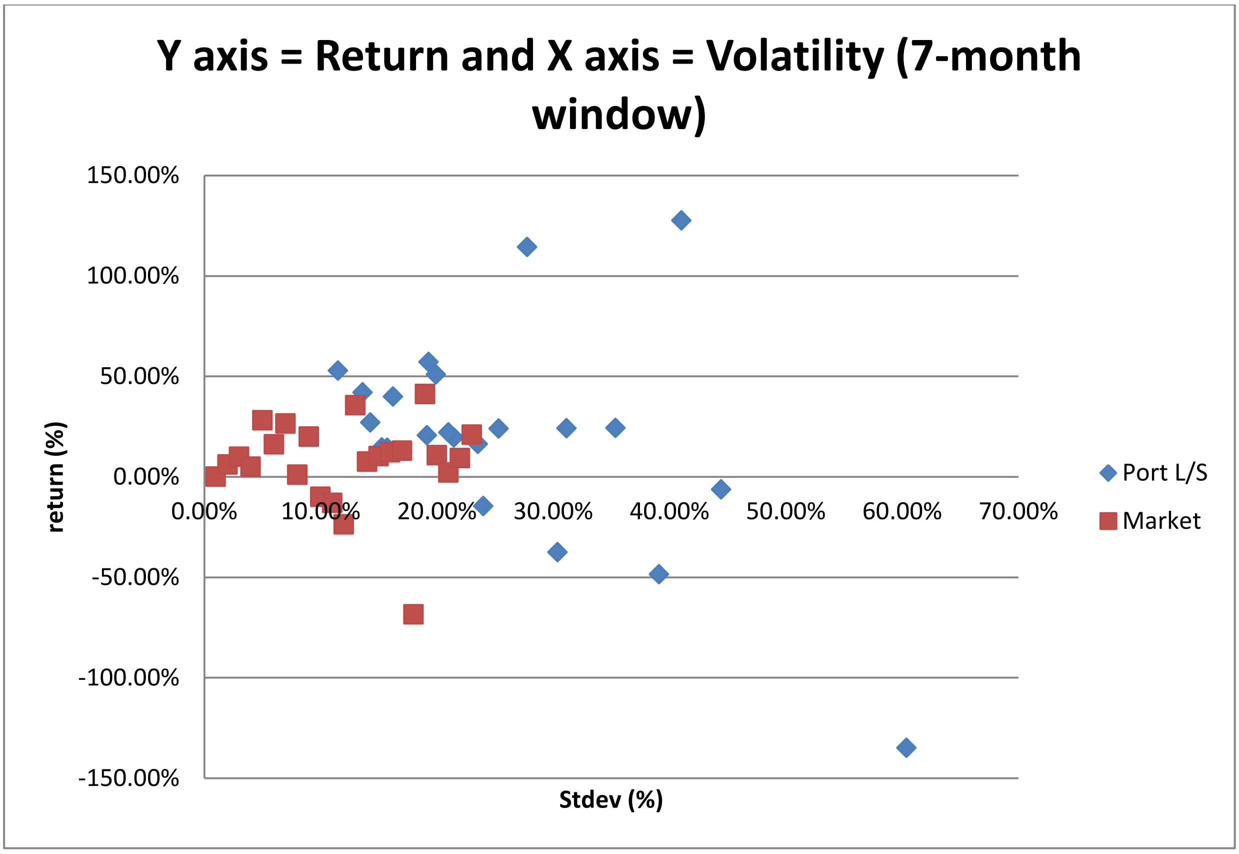

Figure 4.6-31 Scatter diagram return and volatility (7-month window)

Figure 4.6-31 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot, investors will be able to understand that for the same level of risk our strategy is delivering a higher return, as suggested by the concentration on around 20% standard deviation. (Refer to Appendix F.)

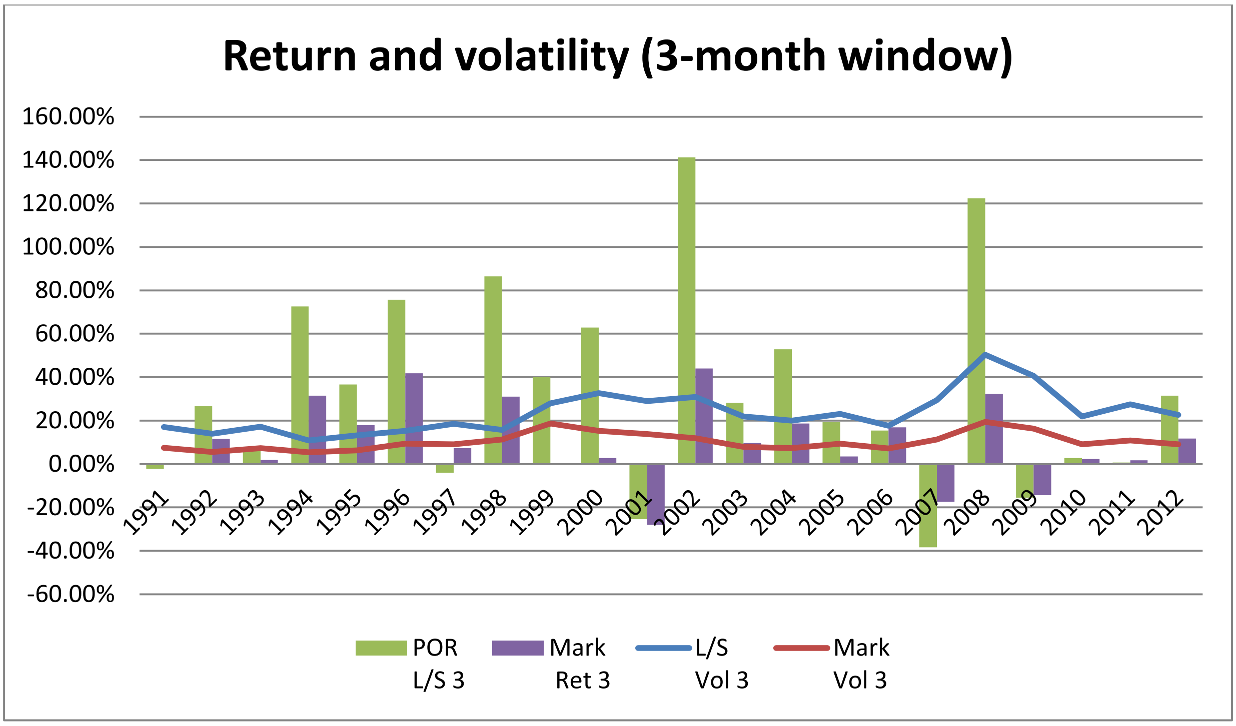

Figure 4.6-32 Return and volatility for long-short portfolio against market (3-month window)

In Figure 4.6-32, we present annualized returns and annualized volatility on a 3-month window horizon. The results are showing that for not a much greater volatility we are able to generate higher returns. For illustration purposes, during periods of high market volatility investors are likely to see return to be negative, for instance in 2007, in 2001 or in 1997. It should also be noted that during those crisis times our portfolio is facing a double volatility on both sides of the portfolio, i.e. the long portfolio and the short portfolio.

As an example, in 2007 the portfolio has a negative return of -38.37% for a volatility of 29.45% whilst the market has a negative return of -17.41% for a volatility 11.36%, meaning that our strategy relative to the market is not very risky even during crisis times.

In the following figure, 4.6-33, we represent a scatter diagram with, in the y-axis, the return of our long-short portfolio against the market and on the x-axis the volatility of our long-short portfolio against the volatility of the market on a 3-month annualized window. (Refer to Appendix F.)

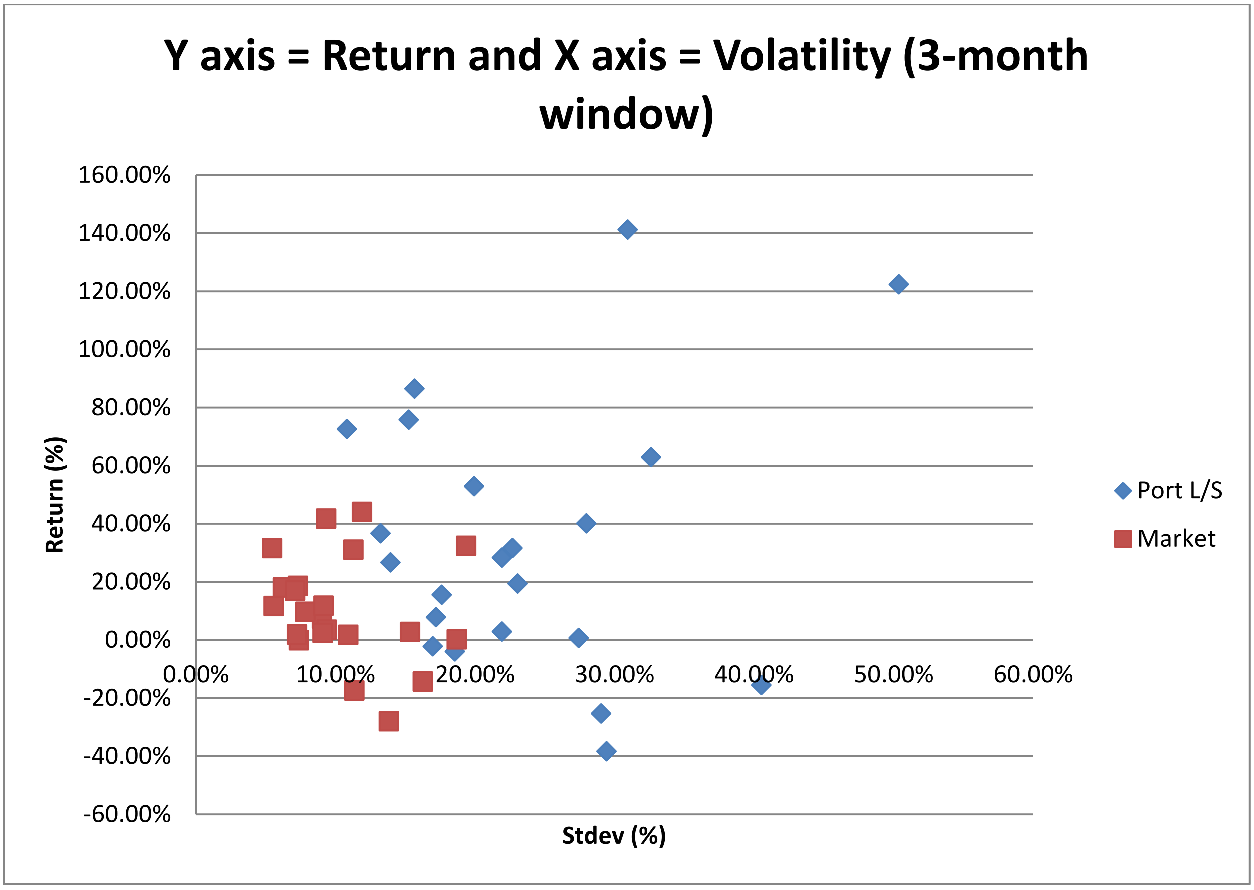

Figure 4.6-33 Scatter diagram return and volatility (3-month window)

Figure 4.6-33 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot, investors will be able to understand that for the same level of risk our strategy is delivering a higher return, as suggested by the concentration on around 20% standard deviation. (Refer to Appendix F.)

4.7 Refinement of Piotroski F-score by removing one criterion

4.7.1 Refinement by removing the lowest percentage criterion

Following our long-short portfolio performance based on using Piotroski F-score, we decided to see whether it was possible to drop one criterion highlighted by the F-score and add a small constraint before buying or shorting stocks to another portfolio based on the rationale that investors might be willing to buy a stock rated with a 7 or an 8 only if this one has had a good rally before portfolio formation; also, the same logic was applied for the short portfolio.

The first step consisted of identifying which criteria were perhaps less significant in generating returns. To do so, we identified firms having positive returns and negative returns within the stocks rated with a 7 and 8 or a 9 and analyzed which criteria contributed the most, i.e. what the firms scored in all criteria (0 to 9).

Eventually, if a firm did not score in a particular criterion but still generated significant return this criterion could potentially be removed from the Piotroski F-score. In both analyses, results suggested that criteria number 7: "Shares outstanding is not greater than the previous year, the firm scores one otherwise it is a zero" is less significant than any other criteria. (Please find below the results from our analysis.) In other words, only 1/3 of the firms scored in F7.

The second step was then to investigate whether by removing these criteria our portfolio was close to generate subsequent return. To do so, we are buying stocks rated with a 7 or an 8 and we are shorting stocks rated with a score of 0 to 3. We will call this portfolio "Portfolio 2" for illustration purposes.

The last step was to add a constraint to this new "Portfolio 2" to see whether it was possible to maximize return and for comparability purposes. Therefore, we have decided to buy or sell stocks on the basis of those that have generated a positive return for the long portfolio and a negative return for the short portfolio before portfolio formation. In other words, in the case of the long portfolio, if the stocks generated a positive return from 0 to 90 days and are rated with a 7 or an 8 than we buy the stocks.

Accordingly, the same approach has been taken on the other side (short side) where we look at negative return for stocks rated 0 to 3 before portfolio formation (0 to 90 days). "Portfolio 3" presented a mix of results.

Solely after investigation, the original portfolio (also called ”Portfolio 1” for simplification purposes) offered better returns and less drawdown, even if regarding the investment window our two other portfolios might reflect better results; also, when taking a look at risk-adjusted metrics “Portfolio 1” is able to offer a better risk-adjusted return to investors. Overall, we draw the conclusion that “Portfolio 1” outperforms “Portfolio 2” and “Portfolio 3”.

This part is described as follows: first we present findings relative to factor F7 and second we compare our three portfolios using different metrics.

Table 4.7-1 Criteria relevancy for stocks rated either by a 7 an 8 or a 9 with a positive return (absolute numbers)

	Total Positive Return Stocks	**F1**	**F2**	**F3**	**F4**	**F5**	**F6**	**F7**	**F8**	**F9**
2012	147	147	147	99	141	104	125	32	142	131
2011	91	91	90	72	87	70	79	27	82	57
2010	113	113	113	98	111	69	98	26	108	88
2009	211	206	211	145	209	116	201	54	195	195
2008	105	105	105	71	103	88	96	29	95	63
2007	37	36	37	29	37	26	29	9	33	34
2006	101	99	101	70	98	64	83	47	89	78
2005	121	120	120	104	118	65	104	57	111	81
2004	159	158	159	142	154	67	126	75	147	124
2003	154	145	154	129	149	79	135	66	135	121
2002	259	252	259	212	255	147	215	102	225	221
2001	61	58	61	45	59	40	51	30	53	48
2000	125	125	125	95	119	84	112	57	112	88
1999	148	146	148	108	134	101	116	79	131	108
1998	133	130	133	101	131	87	97	71	122	108
1997	117	117	117	87	110	67	93	66	106	92
1996	208	205	208	159	197	151	165	104	180	156
1995	159	158	158	124	152	104	123	82	142	113
1994	145	142	145	123	139	97	116	53	125	110
1993	107	106	107	86	103	58	86	48	93	88
1992	106	102	106	88	102	53	92	51	95	75
1991	55	52	55	41	53	33	45	18	53	46

In Table 4.7-1, the left hand side contains the number of stocks with a positive return and the right hand side contains the nine criteria and how many of the stocks score in the different criteria.

Below we display a table in percentage, which is perhaps more representative, where we divide each criterion’s number by the total each year and multiple by 100 in order to get percentages.

If someone wants to interpret this table, the best way is to take an example: for instance, for illustration purposes, only 32 stocks out of 147 stocks in 2012 scored in F7, implying that only

22% of the 147 stocks in 2012 generated a positive return partly due to this criterion, meaning that, if this is recurrent throughout the years, then this criterion could potentially be removed from the selection process.

Table 4.7-2 Criteria relevancy for stocks rated either by a 7 an 8 or a 9 with a positive return (percentage numbers)

	F1	F2	F3	F4	F5	F6	F7	F8	F9
2012	100%	100%	67%	96%	71%	85%	22%	97%	89%
2011	100%	99%	79%	96%	77%	87%	30%	90%	63%
2010	100%	100%	87%	98%	61%	87%	23%	96%	78%
2009	98%	100%	69%	99%	55%	95%	26%	92%	92%
2008	100%	100%	68%	98%	84%	91%	28%	90%	60%
2007	97%	100%	78%	100%	70%	78%	24%	89%	92%
2006	98%	100%	69%	97%	63%	82%	47%	88%	77%
2005	99%	99%	86%	98%	54%	86%	47%	92%	67%
2004	99%	100%	89%	97%	42%	79%	47%	92%	78%
2003	94%	100%	84%	97%	51%	88%	43%	88%	79%
2002	97%	100%	82%	98%	57%	83%	39%	87%	85%
2001	95%	100%	74%	97%	66%	84%	49%	87%	79%
2000	100%	100%	76%	95%	67%	90%	46%	90%	70%
1999	99%	100%	73%	91%	68%	78%	53%	89%	73%
1998	98%	100%	76%	98%	65%	73%	53%	92%	81%
1997	100%	100%	74%	94%	57%	79%	56%	91%	79%
1996	99%	100%	76%	95%	73%	79%	50%	87%	75%
1995	99%	99%	78%	96%	65%	77%	52%	89%	71%
1994	98%	100%	85%	96%	67%	80%	37%	86%	76%
1993	99%	100%	80%	96%	54%	80%	45%	87%	82%
1992	96%	100%	83%	96%	50%	87%	48%	90%	71%
1991	95%	100%	75%	96%	60%	82%	33%	96%	84%
Average	**98%**	**100%**	**78%**	**97%**	**63%**	**83%**	**41%**	**90%**	**77%**

As previously illustrated, Table 4.7-2 describes Table 4.7-1 in terms of percentages. On average only 41% of the companies scored in F7 throughout the years.

Also, it can be noticed that on average F1 and F2, which are ROA (Return On Assets) and CFO (Cash Flow from Operations) respectively, are significantly more relevant than any other criteria, suggesting that companies that have generated positive returns have had a positive ROA and CFO.

Also, it appears that in general criteria that are less significant on average are all related to change in leverage where the firm is signalling its inability to generate sufficient funds internally.

After drafting the hypothesis that potentially factor 7 could be eventually removed, we decided to conduct the same approach for stocks with negative returns. Please refer to the tables below:

Table 4.7-3 Criteria relevancy for stocks rated either by a 7 an 8 or a 9 with a negative return (absolute numbers)

	Total Negative Return Stocks	F1	F2	F3	F4	F5	F6	F7	F8	F9
2012	22	22	22	15	22	16	20	3	19	19
2011	26	26	26	23	25	17	20	8	25	18
2010	74	72	74	66	70	41	66	24	68	59
2009	29	25	29	25	29	13	26	6	27	29
2008	8	8	8	7	7	6	7	2	8	5
2007	129	128	129	96	127	86	112	36	115	108
2006	99	96	99	79	94	62	80	42	87	78
2005	34	33	34	28	34	11	28	19	28	28
2004	42	42	42	32	40	20	34	22	38	34
2003	62	58	62	52	62	31	57	20	56	50
2002	9	8	9	9	7	8	9	1	8	5
2001	102	96	102	69	100	72	89	45	86	87
2000	41	41	41	31	37	25	33	27	37	30
1999	93	92	92	73	86	61	73	43	86	74
1998	106	106	106	74	101	79	82	48	99	89
1997	131	129	130	94	118	100	99	62	116	105
1996	27	26	27	25	23	18	20	15	25	19
1995	44	43	44	30	39	35	34	23	36	34
1994	15	15	15	12	15	9	10	5	14	14
1993	49	48	48	37	43	24	42	29	46	39
1992	54	52	54	38	51	31	44	33	44	43
1991	17	17	17	12	15	13	17	4	17	14

This table, 4.7-3, can be interpreted in the same manner as the one displayed above, such as out of the stocks rated with a 7, an 8 or a 9 only 22 in 2012 generated a negative return and out of those 22 only three scored in F7, emphasizing our previous hypothesis that potentially factor 7 can be avoided.

Table 4.7-4 Criteria relevancy for stocks rated either by a 7 an 8 or a 9 with a negative return (percentage numbers)

	F1	F2	F3	F4	F5	F6	F7	F8	F9
2012	100%	100%	68%	100%	73%	91%	14%	86%	86%
2011	100%	100%	88%	96%	65%	77%	31%	96%	69%
2010	97%	100%	89%	95%	55%	89%	32%	92%	80%
2009	86%	100%	86%	100%	45%	90%	21%	93%	100%
2008	100%	100%	88%	88%	75%	88%	25%	100%	63%
2007	99%	100%	74%	98%	67%	87%	28%	89%	84%
2006	97%	100%	80%	95%	63%	81%	42%	88%	79%
2005	97%	100%	82%	100%	32%	82%	56%	82%	82%
2004	100%	100%	76%	95%	48%	81%	52%	90%	81%
2003	94%	100%	84%	100%	50%	92%	32%	90%	81%
2002	89%	100%	100%	78%	89%	100%	11%	89%	56%
2001	94%	100%	68%	98%	71%	87%	44%	84%	85%
2000	100%	100%	76%	90%	61%	80%	66%	90%	73%
1999	99%	99%	78%	92%	66%	78%	46%	92%	80%
1998	100%	100%	70%	95%	75%	77%	45%	93%	84%
1997	98%	99%	72%	90%	76%	76%	47%	89%	80%
1996	96%	100%	93%	85%	67%	74%	56%	93%	70%
1995	98%	100%	68%	89%	80%	77%	52%	82%	77%
1994	100%	100%	80%	100%	60%	67%	33%	93%	93%
1993	98%	98%	76%	88%	49%	86%	59%	94%	80%
1992	96%	100%	70%	94%	57%	81%	61%	81%	80%
1991	100%	100%	71%	88%	76%	100%	24%	100%	82%
Average	**97%**	**100%**	**79%**	**93%**	**64%**	**84%**	**40%**	**90%**	**79%**

In Table 4.7-4 once again the lowest average percentage throughout the years is F7, which is equal to 40%.

When looking at the literature, researchers such as Bayless and Chaplinsky (1996), Pontiff and Woodgate (2008), or even when you take a deeper look at the work of Myers and Majluk (1984) and Miller and Rock (1985), have all reported some form of cross section in returns with equity issuance.

This results, in other words, in asymmetric information which is considered in our case as a bad signal as in fact firms are signalling their inability to generate sufficient internal funds to service current debt. In fact, it has been suggested that managers may take advantage of issuance when information in the market is low; moreover, when the information is high issuance this will result in a fall in stock prices.

Below we display results for our three portfolios with:

- “Portfolio 1” defined as long Piotroski stocks rated with a 7, an 8 or a 9 and short stocks 0 to 3.
- “Portfolio 2” defined as long Piotroski stocks rated with a 7, an 8 or a 9 and short stocks 0 to 3 after removing shares’ outstanding criteria.
- “Portfolio 3” defined as Portfolio 2 but adding a constraint in the return before portfolio formation. In other words, we are screening stocks in the long portfolio that generated a positive return from 0 to 90 days and, in the case of the short portfolio stocks, that generated a negative return from 0 to 90 days.

4.7.2 Portfolio performances (long-short portfolios)

4.7.2.1 Portfolio performances in terms of returns (12-month window)

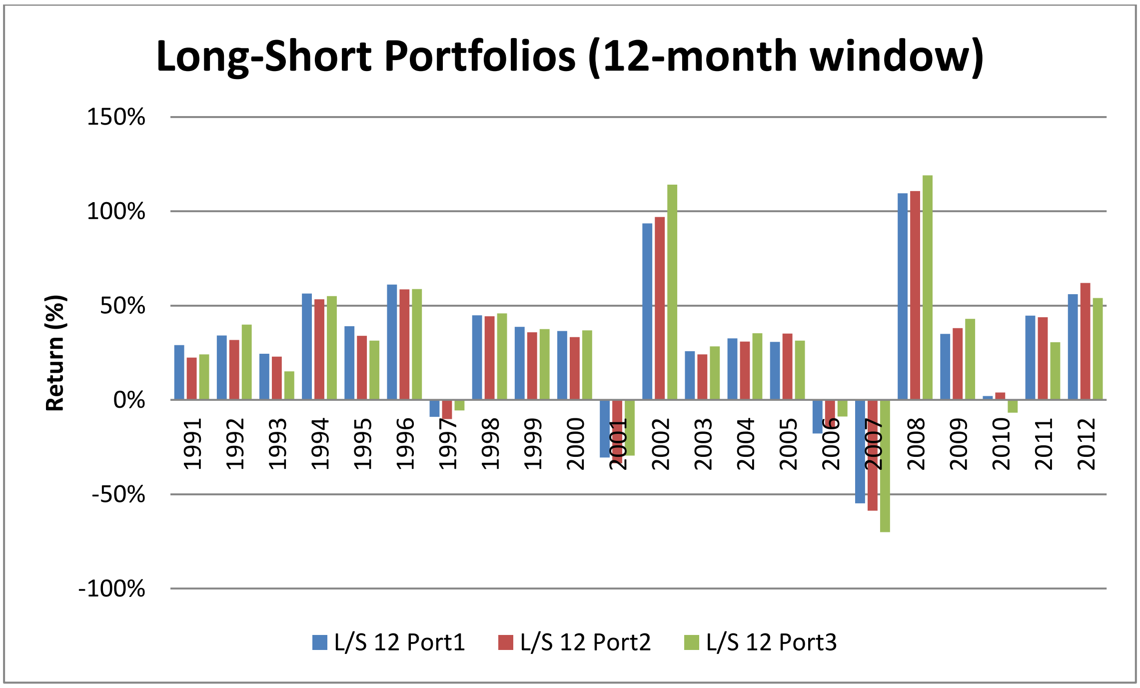

Figure 4.7-1 Long-short portfolios (12-month window)

In Figure 4.7-1 we display our three long-short portfolios’ annual performance over a 12-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to “Portfolio 1”, the red bar to “Portfolio 2” and the green bar to “Portfolio 3”. Please refer to the table below for a better understanding of which portfolio is more efficient.

Table 4.7-5 Statistical summary LS (12-month window)

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	15	10
L/S 12 Port2	7	22	7
L/S 12 Port3	12	15	22

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		68.18%	45.45%
L/S 12 Port2	31.82%		31.82%
L/S 12 Port3	54.55%	68.18%	

Table 4.7-5 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 15 times out of 22 years greater returns than "Portfolio 2"; this corresponds to a percentage of 68.18%, compared to "Portfolio 3"; whilst "Portfolio 1" is only greater 10 times out of 22, which is equal to 45.45%.

In this case we can consider that "Portfolio 3" generates higher returns over the years than "Portfolio 1" and "Portfolio 2".

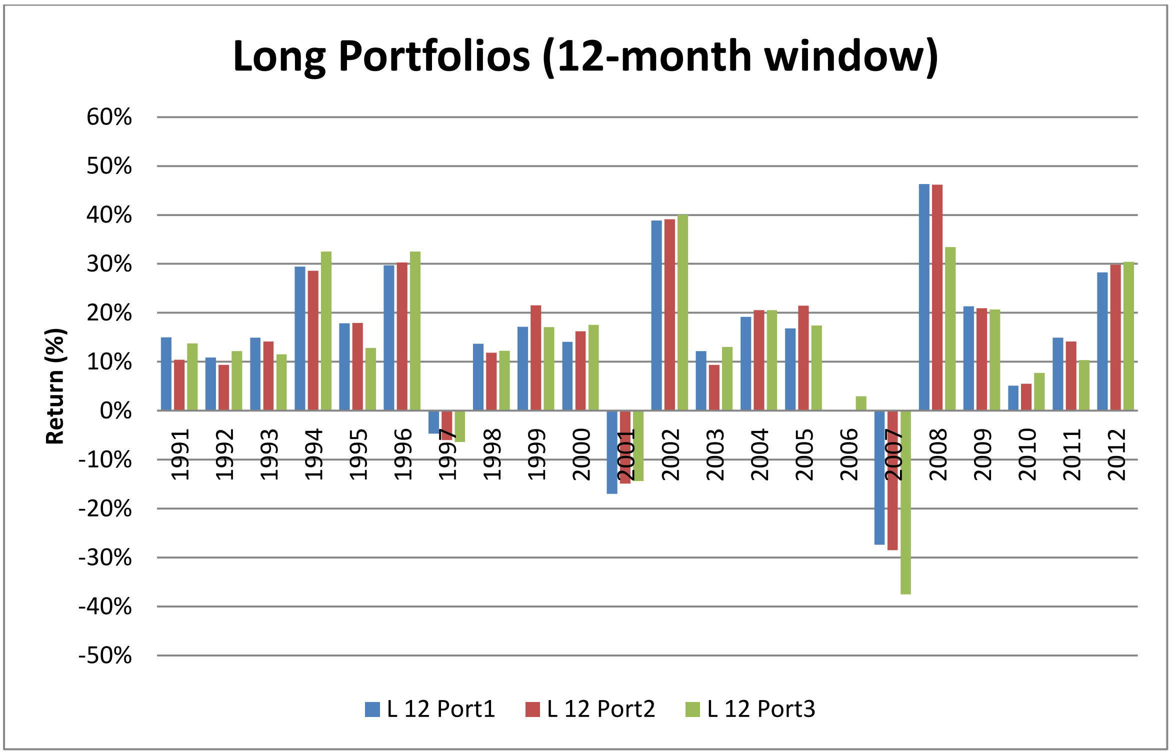

Figure 4.7-2 Long portfolios (12-month window)

We display here in Figure 4.7-2 the behaviour of the three portfolios focusing on the long side to see which one generates higher returns. Once again we will use the table below for statistical description as this gives a better idea of the results.

Table 4.7-6 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port2	L 12 Port3
L 12 Port1	22	11	10
L 12 Port2	11	22	10
L 12 Port3	12	12	22

>	L 12 Port1	L 12 Port2	L 12 Port3
L 12 Port1		50.00%	45.45%
L 12 Port2	50.00%		45.45%
L 12 Port3	54.55%	54.55%	

Table 4.7-6 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 11 times out of 22 years greater returns than "Portfolio 2"; this corresponds to a percentage of 50.00%, compared to "Portfolio 3"; whilst "Portfolio 1" is only greater 10 times out of 22, which is equal to 45.45%.

In this case we can consider that "Portfolio 3" generates higher returns over the years than "Portfolio 1" and "Portfolio 2".

The same approach is done by taking a look at the behaviour of the short portfolio over our three strategies.

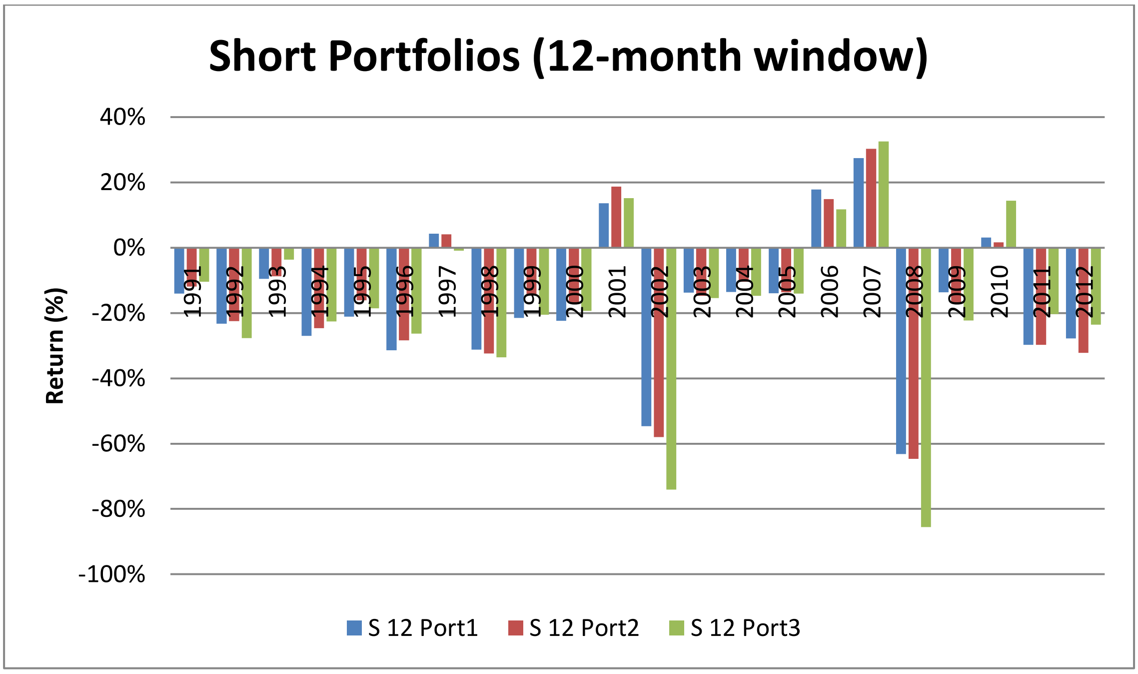

Figure 4.7-3 Short portfolios (12-month window)

This figure, 4.7-3, describes our three portfolios' behaviour on the short side. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 2" and the green bar to "Portfolio 3". Please refer to the table below for statistics on the short portfolio.

Table 4.7-7 Statistical summary S (12-month window)

<	S 12 Port1	S 12 Port2	S 12 Port3
S 12 Port1	22	12	12
S 12 Port2	10	22	8
S 12 Port3	10	14	22

<	S 12 Port1	S 12 Port2	S 12 Port3
S 12 Port1		54.55%	54.55%
S 12 Port2	45.45%		36.36%
S 12 Port3	45.45%	63.64%	

Table 4.7-7 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 11 times out of 22 years greater returns than "Portfolio 2"; this corresponds to a percentage of 50.00%, compared to "Portfolio 3"; whilst "Portfolio 1" is only greater 10 times out of 22, which is equal to 45.45%.

In this case we can consider that "Portfolio 1" generates higher returns over the years than "Portfolio 1" and "Portfolio 2" despite that "Portfolio 3" over "Portfolio 2" might be better than "Portfolio 1" over "Portfolio 2".

4.7.2.2 Portfolio performances in terms of returns (7-month window)

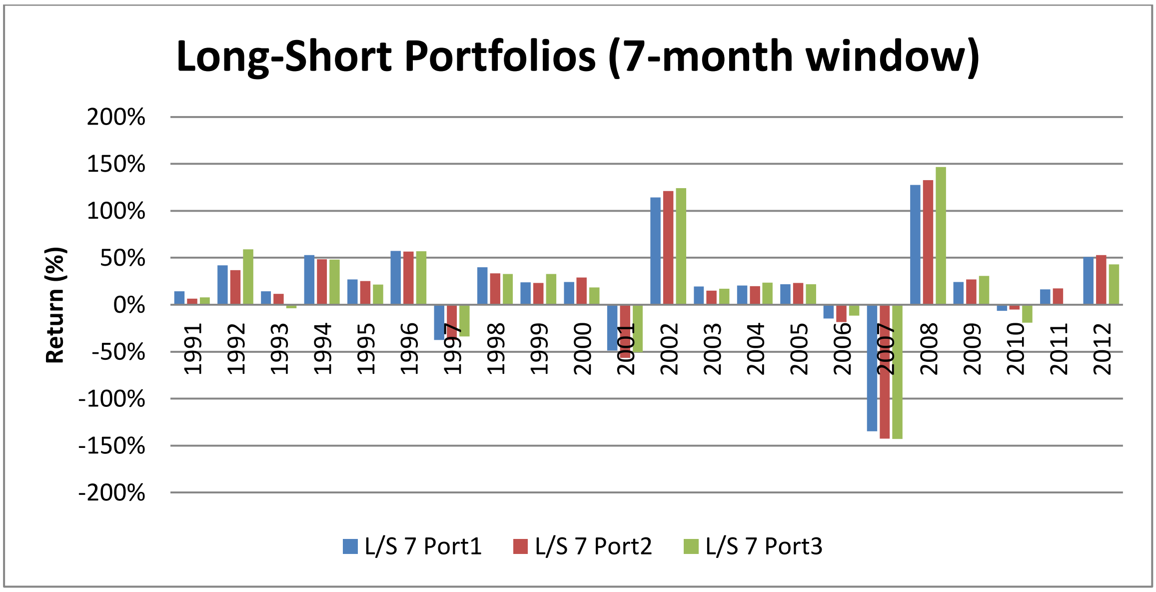

Figure 4.7-4 Long-short portfolios (7-month window)

In this figure, 4.7-4, we display our three long-short portfolios' annual performance over a 7-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 2" and the green bar to "Portfolio 3". Please refer to the table below for a better understanding of which portfolio is more efficient.

Table 4.7-8 Statistical summary LS (7-month window)

>	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3
L/S 7 Port1	22	13	14
L/S 7 Port2	9	22	10
L/S 7 Port3	8	12	22

>	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3
L/S 7 Port1		59.09%	63.64%
L/S 7 Port2	40.91%		45.45%
L/S 7 Port3	36.36%	54.55%	

Table 4.7-8 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 13 times out of 22 years greater returns than "Portfolio 2"; this corresponds to a percentage of 59.09%, compared to "Portfolio 3"; whilst "Portfolio 1" is greater 14 times out of 22, which is equal to 63.64%.

In this case we can consider that "Portfolio 1" generates higher returns over the years than "Portfolio 2" and "Portfolio 3".

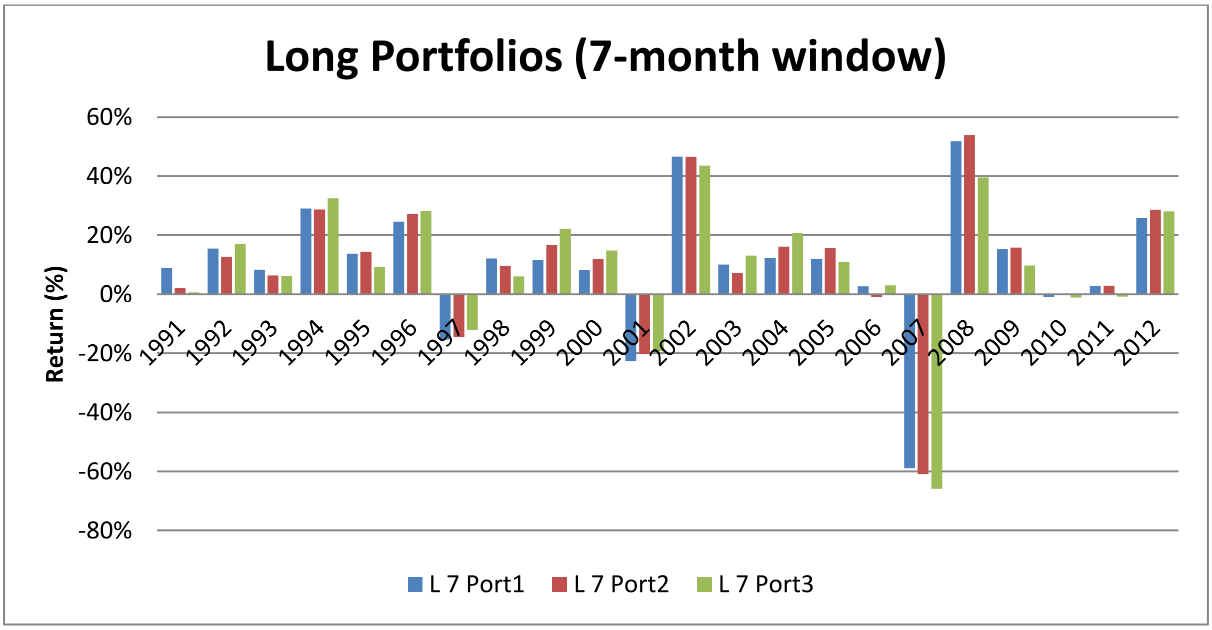

Figure 4.7-5 Long portfolios (7-month window)

We display here in Figure 4.7-5 the behaviour of the three portfolios focusing on the long side to see which one generates higher returns. Once again we will use the table below for statistical description as it gives a better idea of the results.

Table 4.7-9 Statistical summary L (7-month window)

>	**L7 Port1**	**L7 Port2**	**L7 Port3**
L7 Port1	22	9	11
L7 Port2	13	22	12
L7 Port3	11	10	22

>	**L7 Port1**	**L7 Port2**	**L7 Port3**
L 7 Port1		40.91%	50.00%
L 7 Port2	59.09%		54.55%
L 7 Port3	50.00%	45.45%	

Table 4.7-9 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case “Portfolio 2” has generated 13 times out of 22 years greater returns than “Portfolio 1”; this corresponds to a percentage of 59.09%; by contrast to “Portfolio 3”, “Portfolio 2” is only greater 12 times out of 22, which is equal to 54.55%.

In this case we can consider that “Portfolio 2” generates higher returns over the years than “Portfolio 1” and “Portfolio 3”.

The same approach is done by taking a look at the behaviour of the short portfolio over our three strategies.

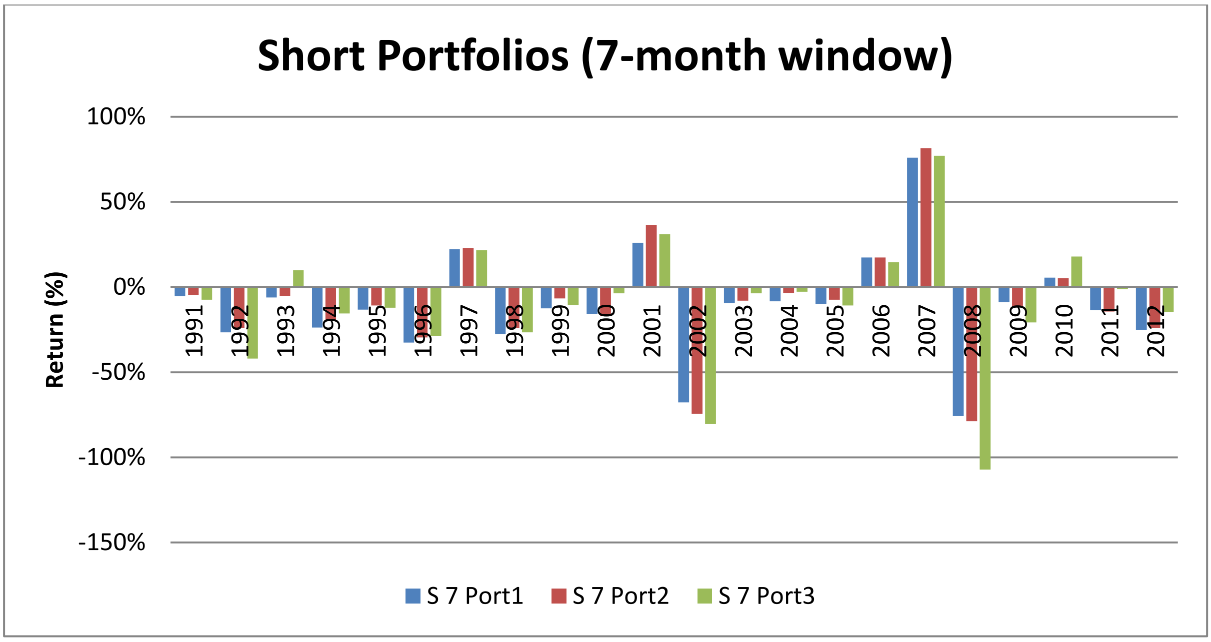

Figure 4.7-6 Short portfolios (7-month window)

This figure, 4.7-6, describes our three portfolios' behaviour on the short side. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 2" and the green bar to "Portfolio 3". Please refer to the table below for statistics on the short portfolio.

Table 4.7-10 Statistical summary L (7-month window)

<	S 7 Port1	S 7 Port2	S 7 Port3
S 7 Port1	22	15	14
S 7 Port2	7	22	9
S 7 Port3	8	13	22

<	S 7 Port1	S 7 Port2	S 7 Port3
S 7 Port1		68.18%	63.64%
S 7 Port2	31.82%		40.91%
S 7 Port3	36.36%	59.09%	

Table 4.7-10 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 15 times out of 22 years greater returns than "Portfolio 2"; this corresponds to a percentage of 68.18; by contrast to "Portfolio 3" where "Portfolio 1" is only greater 14 times out of 22, which is equal to 63.64%.

In this case we can consider that "Portfolio 1" generates higher returns over the years than "Portfolio 2" and "Portfolio 3".

4.7.2.3 Portfolio performances in terms of returns (3-month window)

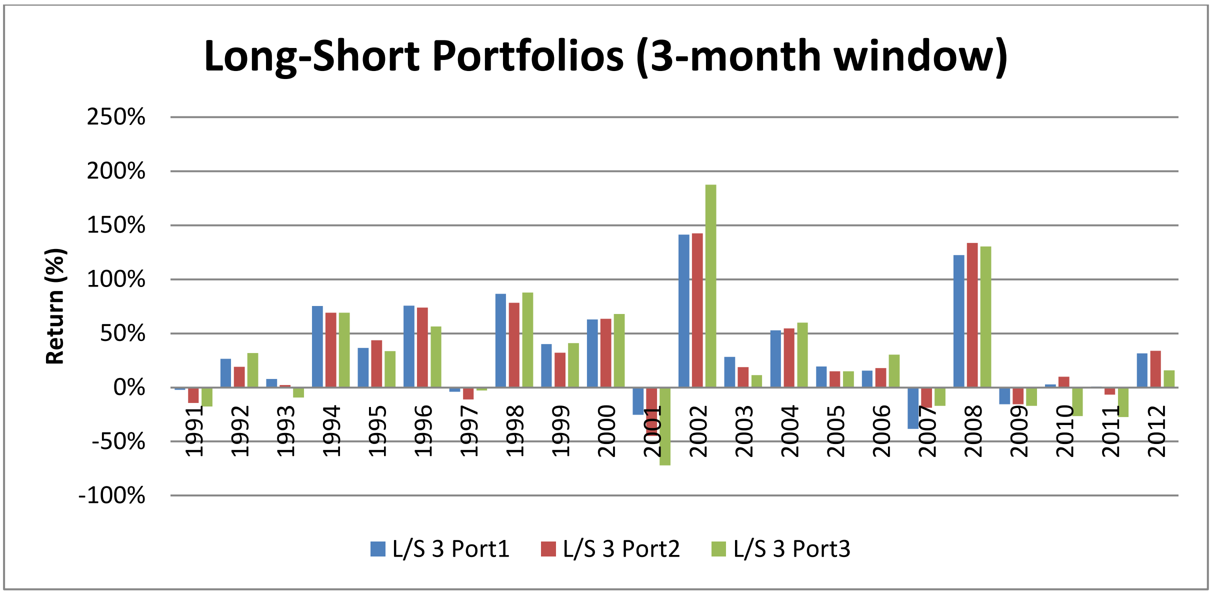

Figure 4.7-7 Long-short portfolios (3-month window)

In this figure, 4.7-7, we display our three long-short portfolios' annual performance over a 3-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 2" and the green bar to "Portfolio 3". Please refer to the table below for a better understanding of which portfolio is more efficient.

Table 4.7-11 Statistical summary LS (3-month window)

>	**L/S 3 Port1**	**L/S 3 Port2**	**L/S 3 Port3**
L/S 3 Port1	22	12	12
L/S 3 Port2	10	22	11
L/S 3 Port3	10	11	22

>	**L/S 3 Port1**	**L/S 3 Port2**	**L/S 3 Port3**
L/S 3 Port1		54.55%	54.55%
L/S 3 Port2	45.45%		50.00%
L/S 3 Port3	45.45%	50.00%	

Table 4.7-11 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 1" has generated 12 times out of 22 years greater returns than "Portfolio 2"; this

corresponds to a percentage of 54.55%, compared to "Portfolio 3", whilst "Portfolio 1" is also greater 12 times out of 22, which is equal to 54.55%.

In this case we can consider that "Portfolio 1" generates higher returns over the years than "Portfolio 2" and "Portfolio 3".

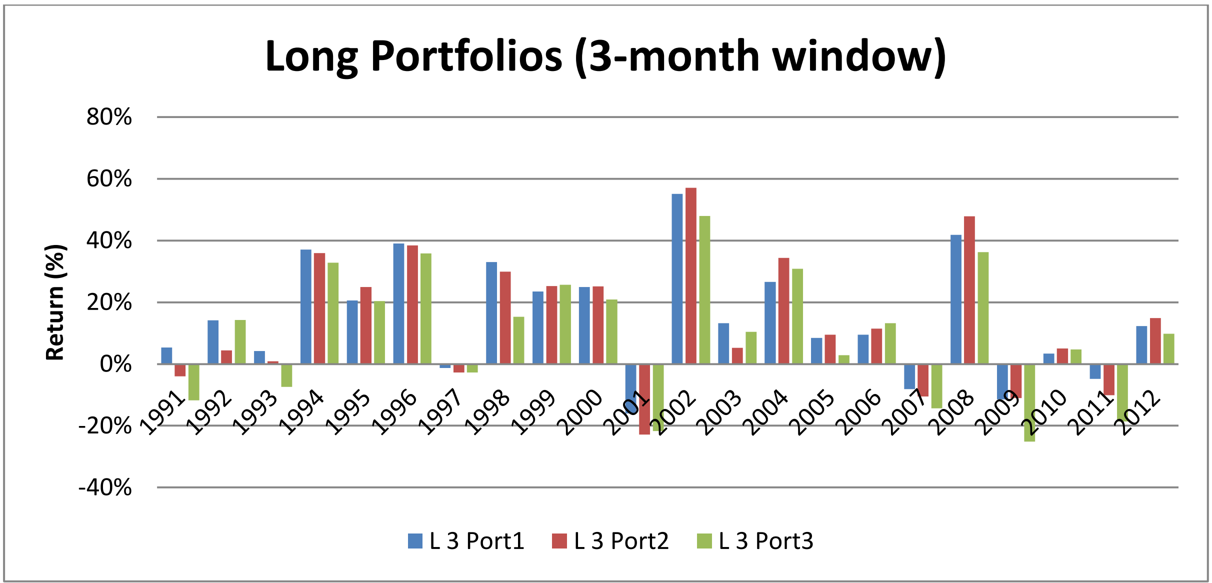

Figure 4.7-8 Long portfolios (3-month window)

We display here in Figure 4.7-8 the behaviour of the three portfolios focusing on the long side to see which one generates higher returns. Once again we will use the table below for statistical description as it gives a better idea of the results.

Table 4.7-12 Statistical summary L (3-month window)

>	L 3 Port1	L 3 Port2	L 3 Port3
L 3 Port1	22	11	17
L 3 Port2	11	22	17
L 3 Port3	5	5	22

>	L 3 Port1	L 3 Port2	L 3 Port3
L 3 Port1		50.00%	77.27%
L 3 Port2	50.00%		77.27%
L 3 Port3	22.73%	22.73%	

Table 4.7-12 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 2" has generated 11 times out of 22 years greater returns than "Portfolio 1"; this

corresponds to a percentage of 50.00; by contrast to “Portfolio 3”, “Portfolio 2” is greater 17 times out of 22, which is equal to 77.27%.

In this case we can consider that both “Portfolio 2” and “Portfolio 1” generate higher returns over the years compared to Portfolio 3”.

The same approach is done by taking a look at the behaviour of the short portfolio over our three strategies.

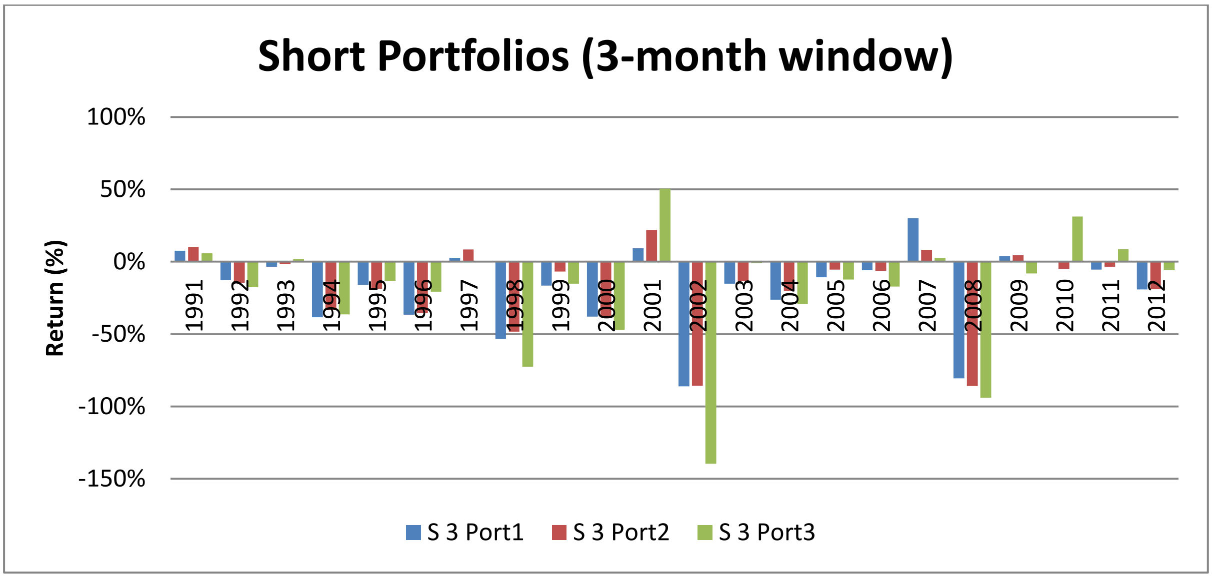

Figure 4.7-9 Short portfolios (3-month window)

This chart in Figure 4.7-9 describes our three portfolios’ behaviour on the short side. The blue bar corresponds to “Portfolio 1”, the red bar to “Portfolio 2” and the green bar to “Portfolio 3”. Please refer to the table below for statistics on the short portfolio.

Table 4.7-13 Statistical summary S (3-month window)

<	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1	22	15	10
S 3 Port2	7	22	8
S 3 Port3	12	14	22

<	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1		68.18%	45.45%
S 3 Port2	31.82%		36.36%
S 3 Port3	54.55%	63.64%	

Table 4.7-13 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this

case “Portfolio 1” has generated 15 times out of 22 years greater returns than “Portfolio 2”; this corresponds to a percentage of 68.18%, by contrast to “Portfolio 3”; whilst “Portfolio 1” is only greater 10 times out of 22, which is equal to 45.45%.

In this case we can consider that “Portfolio 3” generates higher returns over the years than “Portfolio 1” and “Portfolio 2”.

4.7.3 Maximum drawdown (long-short portfolios)

4.7.3.1 Maximum drawdown (12-month window)

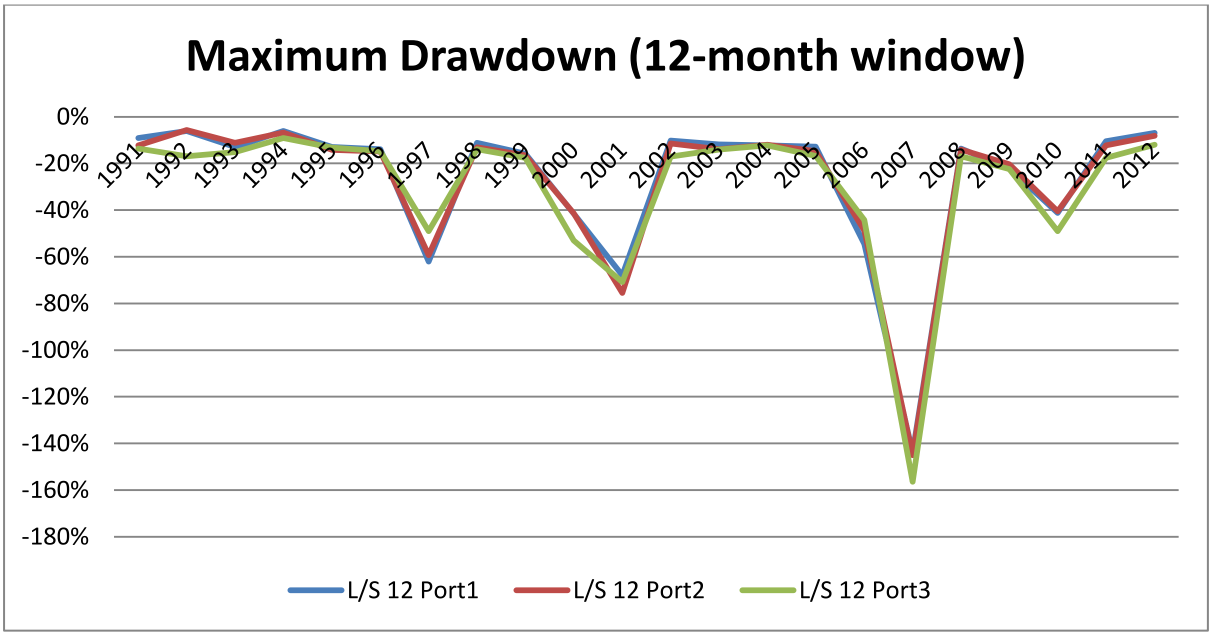

Figure 4.7-10 Maximum drawdown (12-month window)

In this figure, 4.7-10, we present the maximum drawdown of our three portfolios over a 12-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.7-14 Statistical summary LS (12-month window)

<	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	14	19
L/S 12 Port2	8	22	17
L/S 12 Port3	3	5	22

<	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		63.64%	86.36%
L/S 12 Port2	36.36%		77.27%
L/S 12 Port3	13.64%	22.73%	

In this table, 4.7-14, “Portfolio 1” has generated 14 times out of 22 years less drawdowns than “Portfolio 2”; this corresponds to a percentage of 63.64%, by contrast to “Portfolio 3”; whilst “Portfolio 1” generated 19 times out of 22 less drawdowns, which is equal to 86.36%. This suggests that “Portfolio 1” is more efficient at providing investors with less drawdown than “Portfolio 2” and “Portfolio 3”.

4.7.3.2 Maximum drawdown (7-month window)

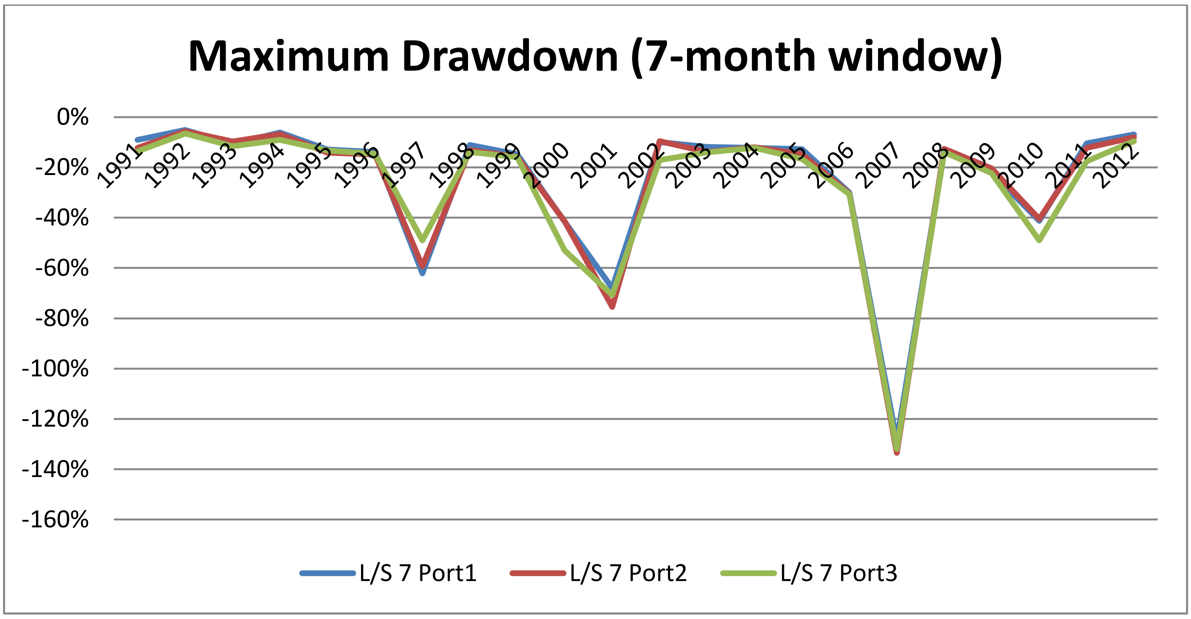

Figure 4.7-11 Maximum drawdown (7-month window)

In this figure, 4.7-11, we present the maximum drawdown of our three portfolios over a 7-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.7-15 Statistical summary LS (7-month window)

<	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3
L/S 7 Port1	22	14	20
L/S 7 Port2	8	22	17
L/S 7 Port3	2	5	22

<	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3
L/S 7 Port1		63.64%	90.91%
L/S 7 Port2	36.36%		77.27%
L/S 7 Port3	9.09%	22.73%	

In this table, 4.7-15, “Portfolio 1” has generated 14 times out of 22 years less drawdowns than “Portfolio 2”; this corresponds to a percentage of 63.64%, by contrast to “Portfolio 3”; whilst

"Portfolio 1" generated 20 times out of 22 less drawdowns, which is equal to 90.91%. This suggests that "Portfolio 1" is more efficient at providing investors with less drawdown than "Portfolio 2" and "Portfolio 3".

4.7.3.3 Maximum drawdown (3-month window)

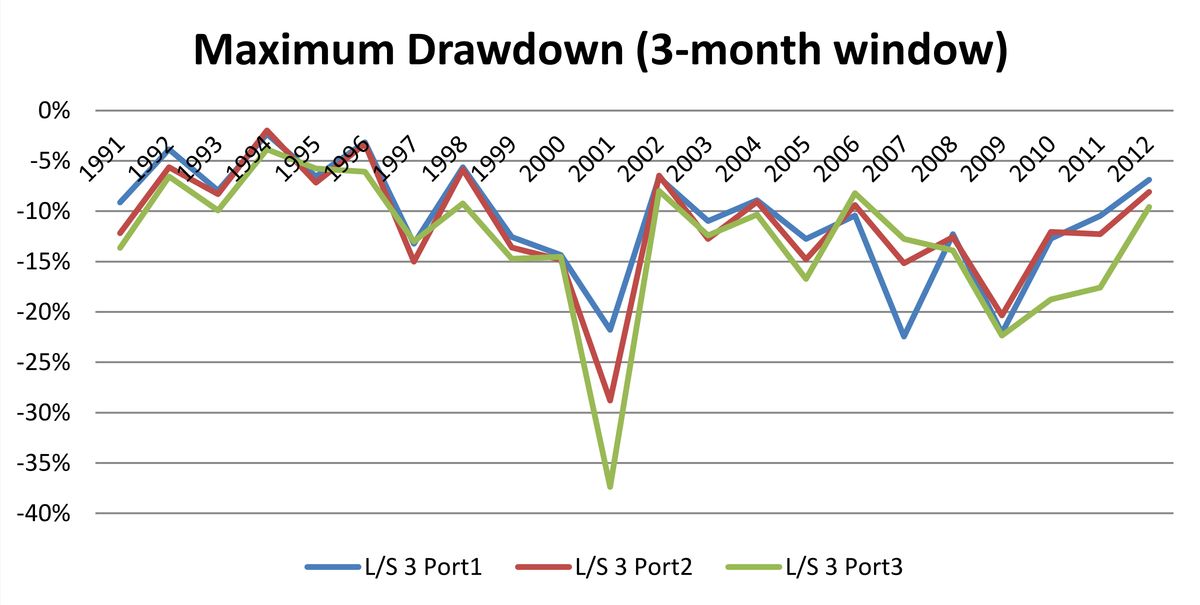

Figure 4.7-12 Maximum drawdown (3-month window)

In this figure, 4.7-12, we present the maximum drawdown of our three portfolios over a 7-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.7-16 Statistical summary LS (3-month window)

<	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
L/S 3 Port1	22	16	18
L/S 3 Port2	6	22	16
L/S 3 Port3	4	6	22

<	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
L/S 3 Port1		72.73%	81.82%
L/S 3 Port2	27.27%		72.73%
L/S 3 Port3	18.18%	27.27%	

In this table, 4.7-16, "Portfolio 1" has generated 16 times out of 22 years less drawdowns than "Portfolio 2"; this corresponds to a percentage of 72.73%, by contrast to "Portfolio 3"; whilst "Portfolio 1" generated 18 times out of 22 less drawdowns, which is equal to 81.82%. This suggests that “Portfolio 1” is more efficient at providing investors with less drawdown than “Portfolio 2” and “Portfolio 3”.

4.7.4 Risk-adjusted measures (long-short portfolios)

4.7.4.1 Sharpe ratio (12-month window)

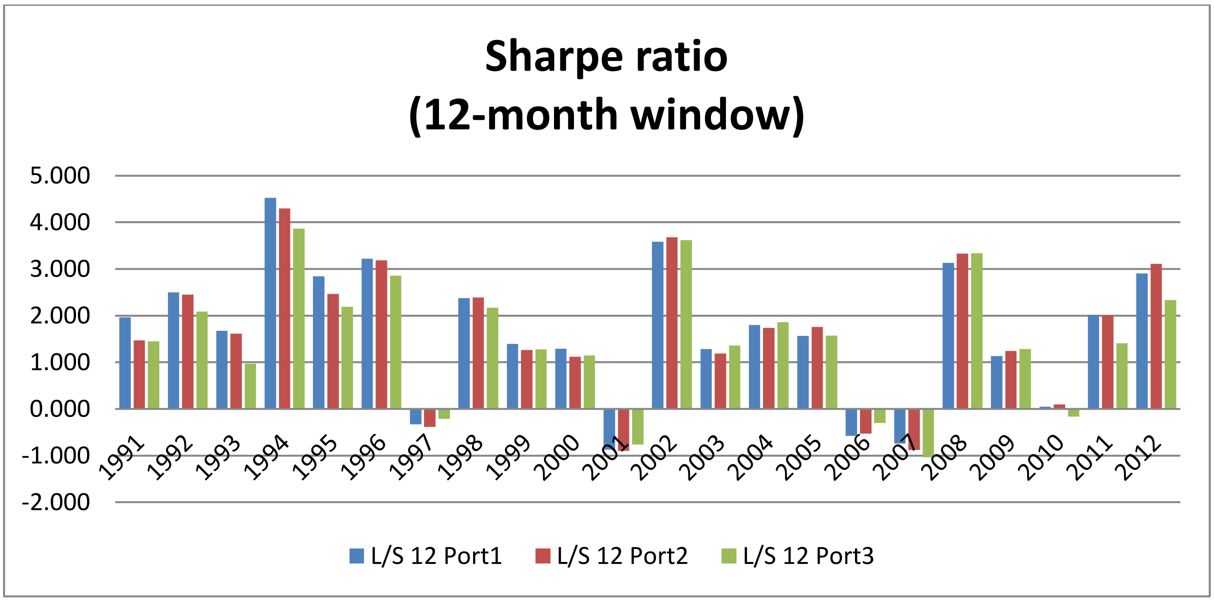

Figure 4.7-13 Sharpe ratio (12-month window)

In this figure, 4.7-13, the Sharpe ratio is used to express how much return is achieved for the amount of risk taken in an investment; when interpreting Sharpe ratio investors look at the highest one, as the higher the ratio the better the fund. Once again we try by using some forms of summary statistics to see which portfolio is better at generating higher Sharpe ratios.

Table 4.7-17 Statistical summary LS (12-month window)

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	14	13
L/S 12 Port2	8	22	13
L/S 12 Port3	9	9	22

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		63.64%	59.09%
L/S 12 Port2	36.36%		59.09%
L/S 12 Port3	40.91%	40.91%	

In this table, 4.7-17, “Portfolio 1” has generated 14 times out of 22 years greater Sharpe ratios than “Portfolio 2”; this corresponds to a percentage of 63.64%, by contrast to “Portfolio 3”; whilst “Portfolio 1” generated 13 times out of 22 greater Sharpe ratios, which is equal to 59.09%.

This suggests that “Portfolio 1” is more efficient at providing investors with higher Sharpe ratios than “Portfolio 2” and “Portfolio 3”.

4.7.4.2 Sharpe ratio (7-month window)

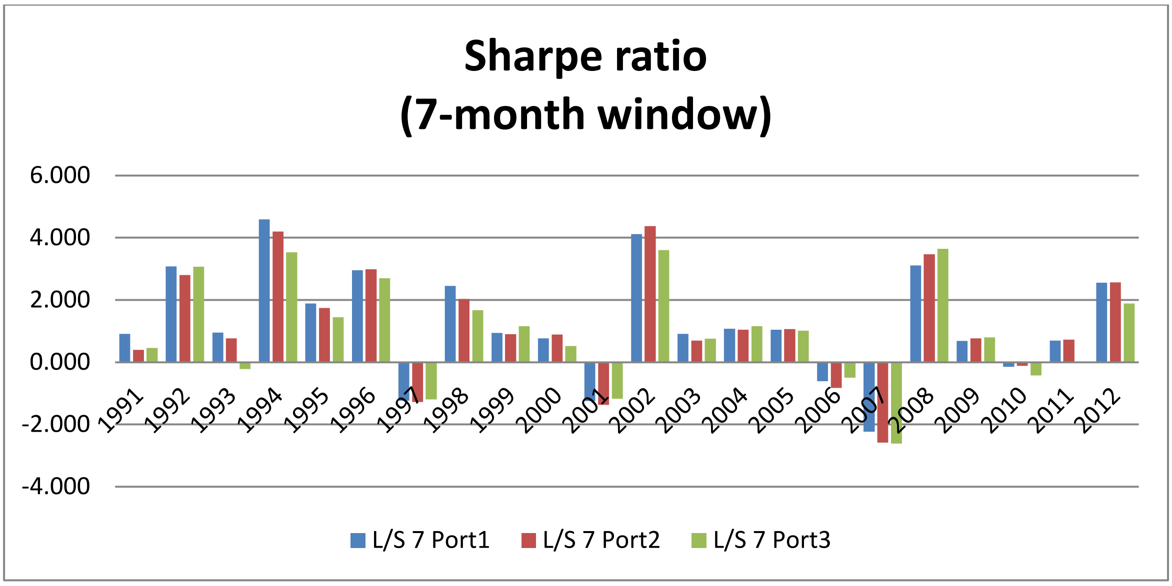

Figure 4.7-14 Sharpe ratio (7-month window)

Table 4.7-18 Statistical summary LS (7-month window)

>	**L 7 Port1**	**L 7 Port2**	**L 7 Port3**
L 7 Port1	22	13	15
L 7 Port2	9	22	12
L 7 Port3	7	10	22

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1		59.09%	68.18%
L 7 Port2	40.91%		54.55%
L 7 Port3	31.82%	45.45%	

In this table, 4.7-18, “Portfolio 1” has generated 13 times out of 22 years greater Sharpe ratios than “Portfolio 2”; this corresponds to a percentage of 59.09%, by contrast to “Portfolio 3”; whilst “Portfolio 1” generated 15 times out of 22 greater Sharpe ratios, which is equal to 68.18%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Sharpe ratios than “Portfolio 2” and “Portfolio 3”.

4.7.4.3 Sharpe ratio (3-month window)

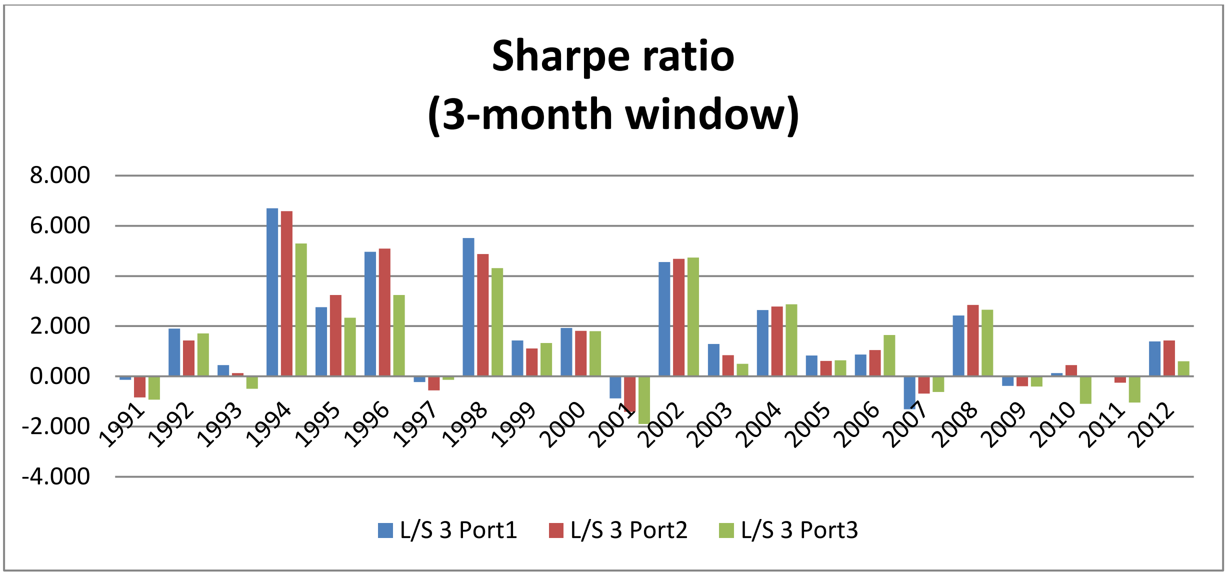

Figure 4.7-15 Sharpe ratio (3-month window)

Table 4.7-19 Statistical summary LS (3-month window)

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1	22	13	16
S 3 Port2	9	22	14
S 3 Port3	6	8	22

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1		59.09%	72.73%
S 3 Port2	40.91%		63.64%
S 3 Port3	27.27%	36.36%	

In this table, 4.7-19, “Portfolio 1” has generated 13 times out of 22 years greater Sharpe ratios than “Portfolio 2”; this corresponds to a percentage of 59.09%, by contrast to “Portfolio 3”; whilst “Portfolio 1” generated 16 times out of 22 greater Sharpe ratios, which is equal to 72.73%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Sharpe ratios than “Portfolio 2” and “Portfolio 3”.

4.7.4.4 Treynor ratio (12-month window)

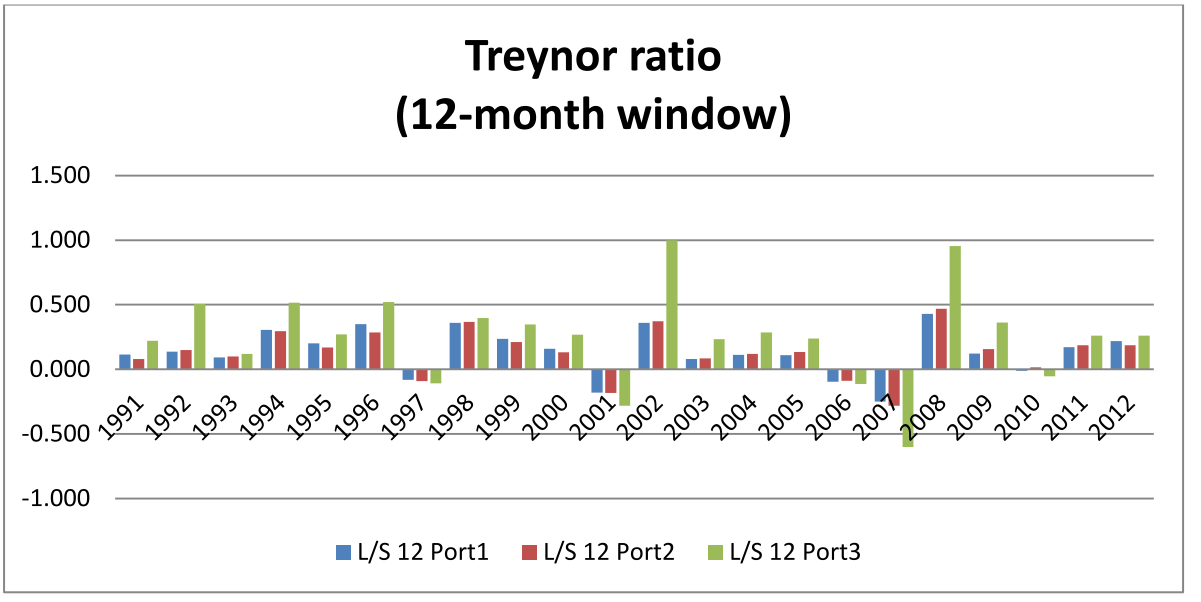

Figure 4.7-16 Treynor ratio (12-month window)

In this Figure 4.7-16, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar returns. Please refer to the table below for comparative purposes between portfolios.

Table 4.7-20 Statistical summary LS (12-month window)

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	10	5
L/S 12 Port2	12	22	5
L/S 12 Port3	17	17	22

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		45.45%	22.73%
L/S 12 Port2	54.55%		22.73%
L/S 12 Port3	77.27%	77.27%	

In this table, 4.7-20, “Portfolio 3” has generated 17 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 77.27%. The same is achieved from “Portfolio 3” to “Portfolio 2”, which generated 16 times out of 22 greater Treynor ratios, which is equal to 72.73%. This suggests that “Portfolio 3” is more efficient at providing investors with higher Treynor ratios than “Portfolio 2” and “Portfolio 3”.

4.7.4.5 Treynor ratio (7-month window)

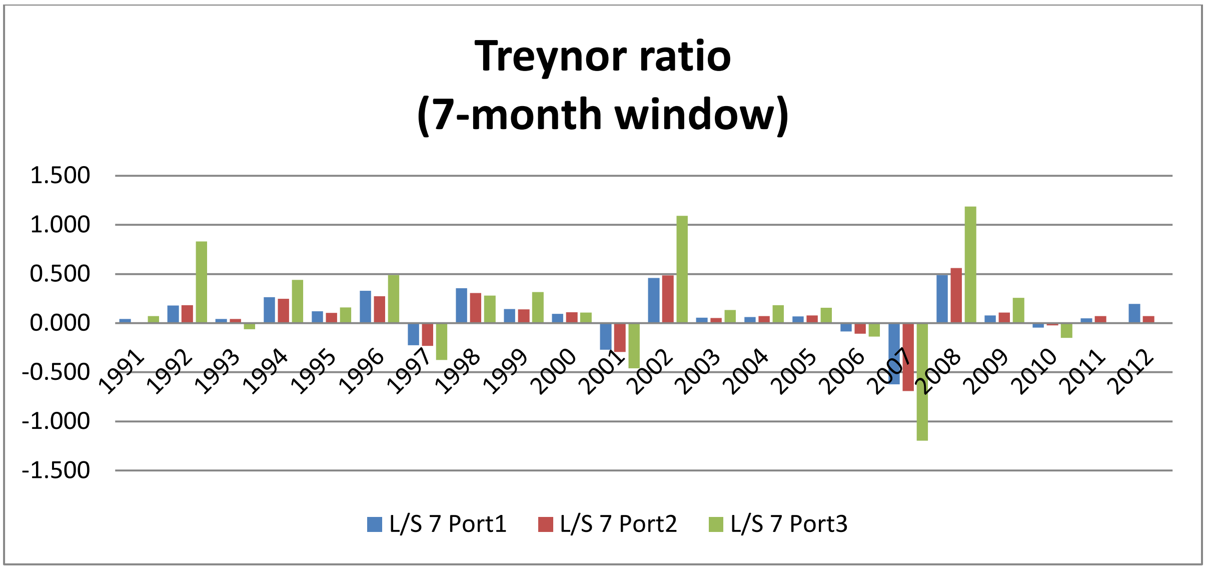

Figure 4.7-17 Treynor ratio (7-month window)

Table 4.7-21 Statistical summary LS (7-month window)

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1	22	13	9
L 7 Port2	9	22	10
L 7 Port3	13	12	22

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1		59.09%	40.91%
L 7 Port2	40.91%		45.45%
L 7 Port3	59.09%	54.55%	

In this table, 4.7-21, “Portfolio 3” has generated 13 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 59.09%, whereas, compared to “Portfolio 2”, “Portfolio 3” generated 12 times out of 22 greater Treynor ratios, which is equal to 54.55%. This suggests that “Portfolio 3” is more efficient at providing investors with higher Treynor ratios than “Portfolio 2” and “Portfolio 3”.

4.7.4.6 Treynor ratio (3-month window)

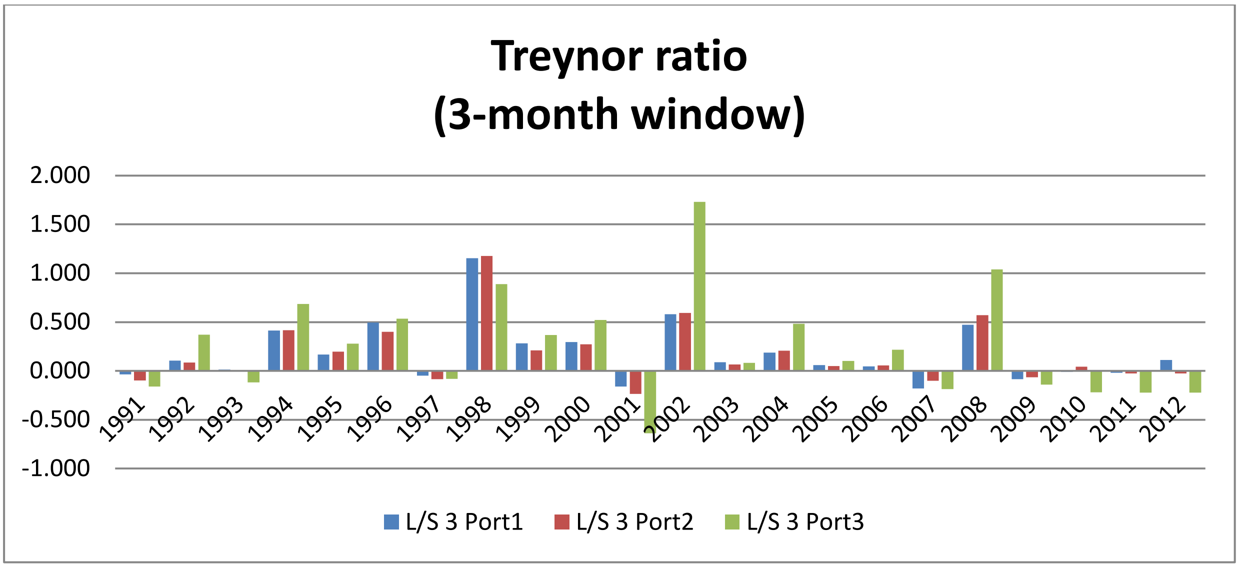

Figure 4.7-18 Treynor ratio (3-month window)

Table 4.7-22 Statistical summary LS (3-month window)

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1	22	12	11
S 3 Port2	10	22	9
S 3 Port3	11	13	22

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1		54.55%	50.00%
S 3 Port2	45.45%		40.91%
S 3 Port3	50.00%	59.09%	

In this table, 4.7-22, “Portfolio 3” has generated 11 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 50.00%, whereas, compared to “Portfolio 2”, “Portfolio 3” generated 13 times out of 22 greater Treynor ratios, which is equal to 59.09%. This suggests that “Portfolio 3” is more efficient at providing investors with higher Treynor ratios than “Portfolio 2” and “Portfolio 3”.

4.1.1.1 Information ratio (12-month window)

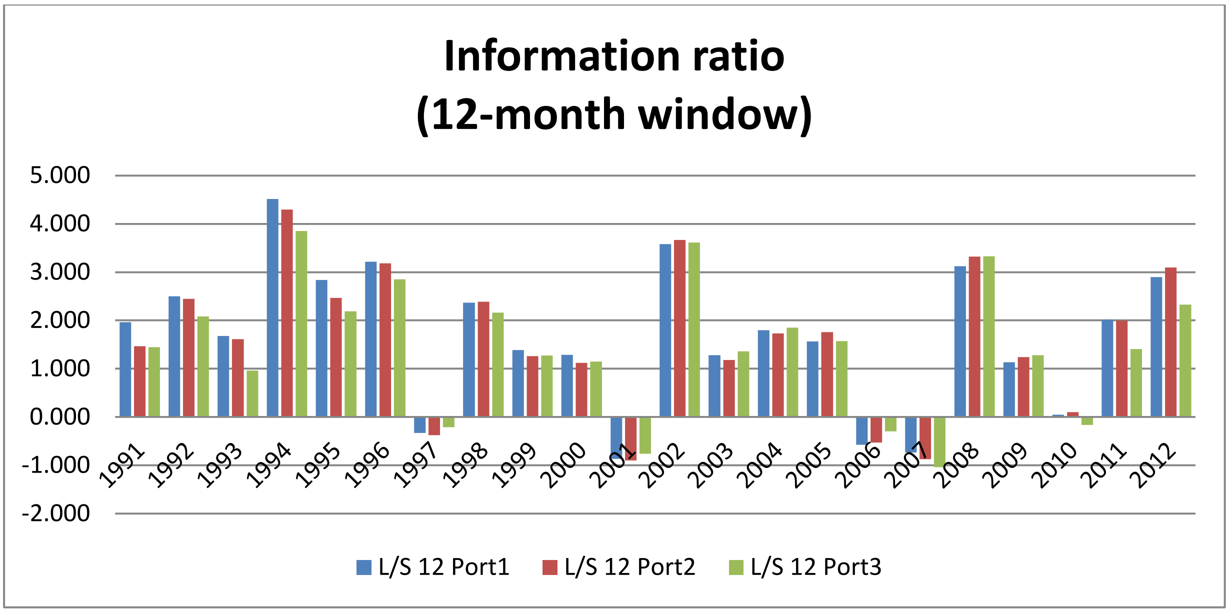

Figure 4.7-19 Information ratio (12-month window)

In this figure, 4.7-19, the Information ratio is used to compare portfolios using the same investment style; the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. Please refer to the table below for comparative purposes between portfolios.

Table 4.7-23 Statistical summary LS (12-month window)

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	14	13
L/S 12 Port2	8	22	13
L/S 12 Port3	9	9	22

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		63.64%	59.09%
L/S 12 Port2	36.36%		59.09%
L/S 12 Port3	40.91%	40.91%	

In this table, 4.7-23, “Portfolio 1” has generated 14 times out of 22 years greater Information ratios than “Portfolio 2”; this corresponds to a percentage of 63.64%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 13 times out of 22 greater Information ratios, which is equal to 59.09%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Information ratios than “Portfolio 2” and “Portfolio 3”.

4.1.1.2 Information ratio (7-month window)

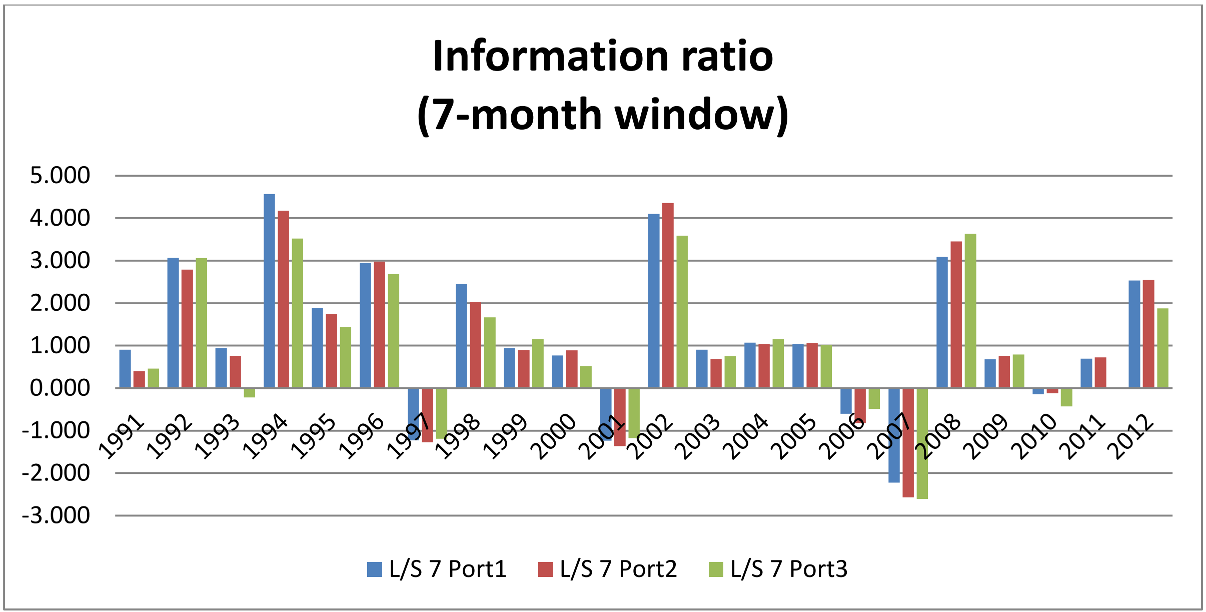

Figure 4.7-20 Information ratio (7-month window)

Table 4.7-24 Statistical summary LS (7-month window)

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1	22	13	15
L 7 Port2	9	22	12
L 7 Port3	7	10	22

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1		59.09%	68.18%
L 7 Port2	40.91%		54.55%
L 7 Port3	31.82%	45.45%	

In this table, 4.7-24, “Portfolio 1” has generated 13 times out of 22 years greater Information ratios than “Portfolio 2”; this corresponds to a percentage of 59.09%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 15 times out of 22 greater Information ratios, which is equal to 68.18%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Information ratios than “Portfolio 2” and “Portfolio 3”.

4.1.1.3 Information ratio (3-month window)

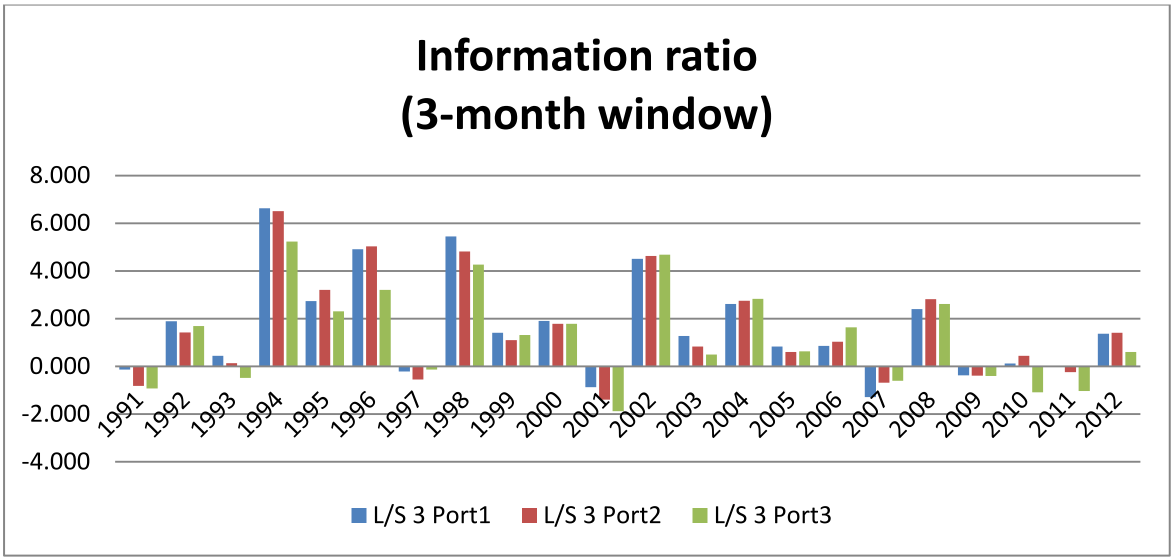

Figure 4.7-21 Information ratio (3-month window)

Table 4.7-25 Statistical summary LS (3-month window)

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1	22	13	16
S 3 Port2	9	22	14
S 3 Port3	6	8	22

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1		59.09%	72.73%
S 3 Port2	40.91%		63.64%
S 3 Port3	27.27%	36.36%	

In this table, 4.7-25, “Portfolio 1” has generated 13 times out of 22 years greater Information ratios than “Portfolio 2”; this corresponds to a percentage of 59.09%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 16 times out of 22 greater Sortino ratios, which is equal to 72.73%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Information ratio than “Portfolio 2” and “Portfolio 3”.

4.1.1.4 Sortino ratio (12-month window)

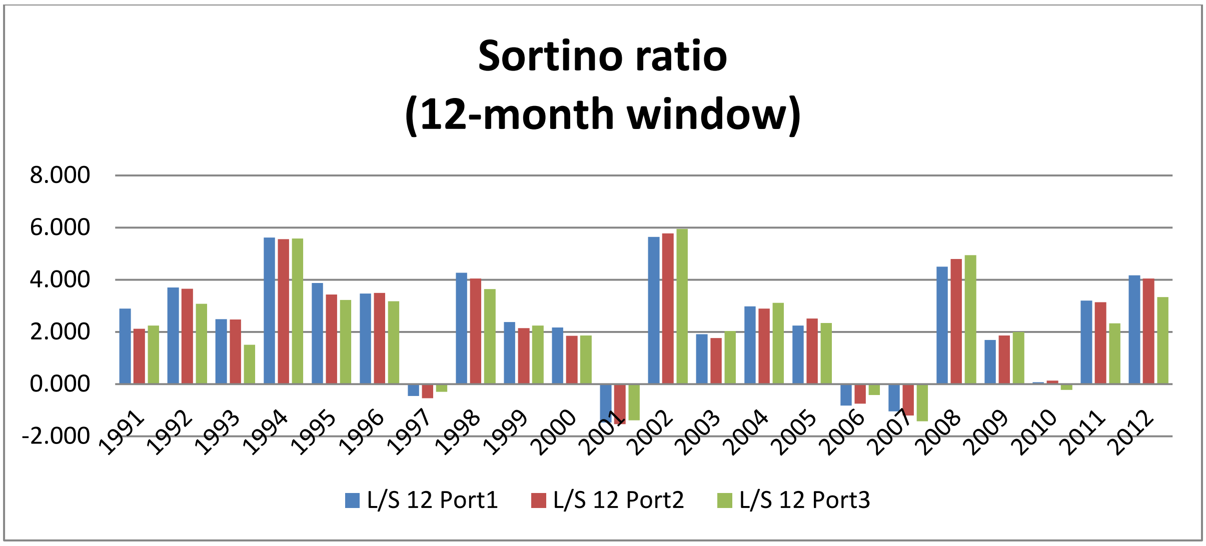

Figure 4.7-22 Sortino ratio (12-month window)

In this figure, 4.7-22, the Sortino ratio which replaces the volatility in the Sharpe ratio with a measure of downside deviations is used to evaluate which portfolio is better at generating higher Sortino ratio. Please refer to the table below for comparative purposes.

Table 4.7-26 Statistical summary LS (12-month window)

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1	22	15	13
L/S 12 Port2	7	22	10
L/S 12 Port3	9	12	22

>	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3
L/S 12 Port1		68.18%	59.09%
L/S 12 Port2	31.82%		45.45%
L/S 12 Port3	40.91%	54.55%	

In this table, 4.7-26, “Portfolio 1” has generated 15 times out of 22 years greater Sortino ratios than “Portfolio 2”; this corresponds to a percentage of 68.18%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 13 times out of 22 greater Sortino ratios, which is equal to 59.09%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios than “Portfolio 2” and “Portfolio 3”.

4.1.1.5 Sortino ratio (7-month window)

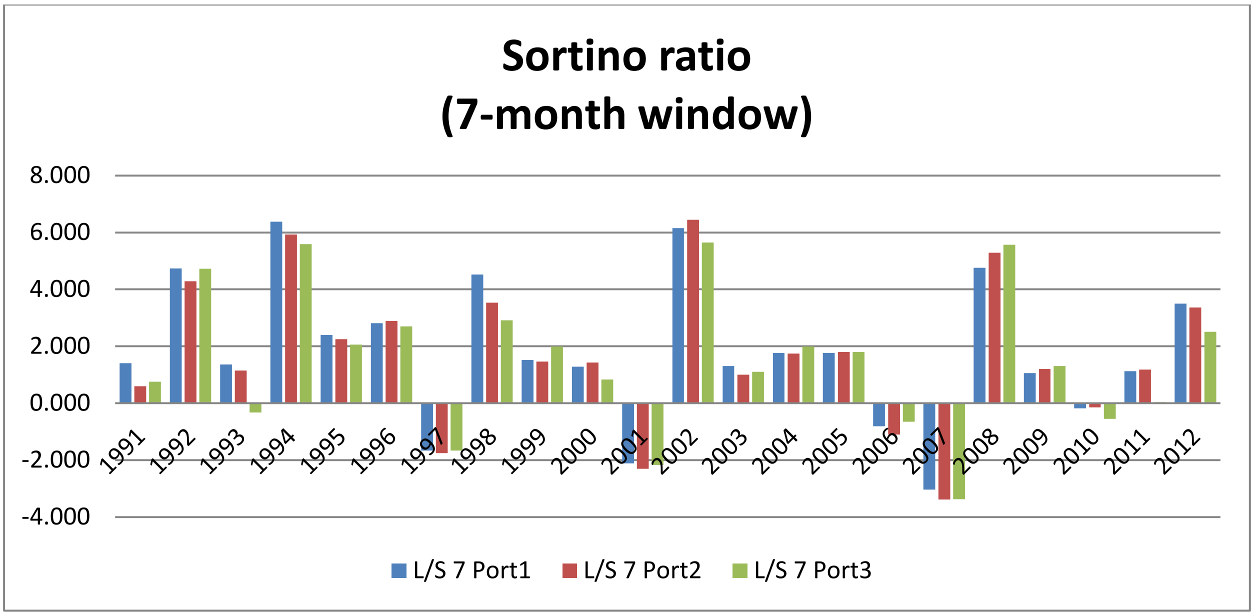

Figure 4.7-23 Sortino ratio (7-month window)

Table 4.7-27 Statistical summary LS (7-month window)

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1	22	14	16
L 7 Port2	8	22	11
L 7 Port3	6	11	22

>	L 7 Port1	L 7 Port2	L 7 Port3
L 7 Port1		63.64%	72.73%
L 7 Port2	36.36%		50.00%
L 7 Port3	27.27%	50.00%	

In this table, 4.7-27, “Portfolio 1” has generated 14 times out of 22 years greater Sortino ratios than “Portfolio 2”; this corresponds to a percentage of 63.64%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 16 times out of 22 greater Sortino ratios, which is equal to 72.73%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios than “Portfolio 2” and “Portfolio 3”.

4.1.1.6 Sortino ratio (3-month window)

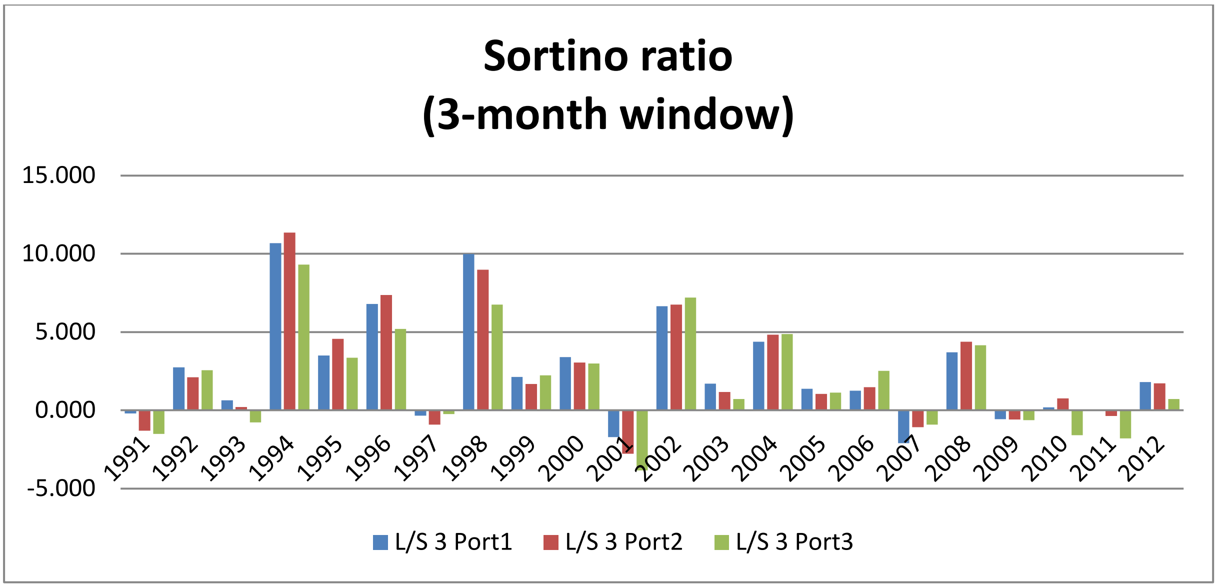

Figure 4.7-24 Sortino ratio (3-month window)

Table 4.7-28 Statistical summary LS (3-month window)

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1	22	13	15
S 3 Port2	9	22	14
S 3 Port3	7	8	22

>	S 3 Port1	S 3 Port2	S 3 Port3
S 3 Port1		59.09%	68.18%
S 3 Port2	40.91%		63.64%
S 3 Port3	31.82%	36.36%	

In this table, 4.7-28, “Portfolio 1” has generated 13 times out of 22 years greater Sortino ratios than “Portfolio 2”; this corresponds to a percentage of 59.09%, whereas, compared to “Portfolio 3”, “Portfolio 1” generated 15 times out of 22 greater Sortino ratios, which is equal to 68.18%. This suggests that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios than “Portfolio 2” and “Portfolio 3”.

4.8 Refinement of Piotroski F-score by removing three criteria

4.8.1 Refinement by removing the highest percentage criteria

Due to unsatisfactory results we decided to rerun the criteria relevancy matrix focusing on the whole sample. We create a long portfolio based on a contrary hypothesis to the one above: instead of dropping the factor with the lowest percentage we drop the highest one, implying that it is more difficult for a company to score in those criteria with the lowest percentage.

Eventually, this should shift the distribution earned by a simple Piotroski approach and, if efficient, investors will be able to focus on our refinement of the Piotroski score.

For illustration purposes we compare our new long portfolio against the long "Portfolio 1", which is a simple use of Piotroski F-score 7 to 9. Our new long portfolio will consist of buying stocks rated with a 6 out of a score where the maximum a firm can obtain is a score of 6 as we removed 3 criteria such as F1, F2 and F4 of Piotroski F-score.

Please refer to the table below for descriptive results on the relevancy of the criteria; also, notice the symmetry percentage-wise regardless of whether they generated positive or negative return.

Table 4.8-1 Criteria relevancy for all stocks regardless of their F-score with a positive return (Absolute numbers)

	Total Positive Return Stocks	F1	F2	F3	F4	F5	F6	F7	F8	F9
1991	558	482	543	118	501	136	146	51	163	180
1992	503	428	476	268	441	170	222	125	272	235
1993	491	411	472	245	427	171	213	115	268	278
1994	767	697	725	375	650	218	257	105	358	294
1995	725	645	679	357	586	270	314	143	352	290
1996	841	757	795	463	708	296	374	209	414	362
1997	406	363	385	200	346	166	172	119	239	179
1998	462	391	439	192	385	217	169	111	235	278
1999	538	501	522	256	470	236	223	101	272	278
2000	513	464	483	242	428	195	234	65	221	203
2001	223	181	211	86	196	94	115	42	78	124
2002	605	491	571	333	540	234	293	116	313	402
2003	581	504	546	312	513	173	324	90	280	271
2004	564	518	537	347	480	127	266	123	291	214
2005	581	529	554	322	503	179	248	110	238	188
2006	373	349	356	201	295	130	192	56	189	164
2007	169	142	162	72	146	76	73	17	71	86
2008	602	474	569	215	508	320	329	56	244	205
2009	1005	802	981	398	943	297	599	118	549	778
2010	755	691	729	486	654	237	351	67	467	326
2011	919	829	875	483	760	359	393	58	381	333
2012	976	853	933	413	845	376	440	74	492	558

In Table 4.8-1 we show the number of stocks with a positive return that have scored in each F-score criterion. The following table displays the same type of picture but instead we are looking at percentage figures to get a better idea.

In this table it can be noticed that, for example, only 51 companies out of 558 in 1991 scored in F7; in other words, only 9% of the 558 stocks scored in this criterion.

Table 4.8-2 Criteria relevancy for all stocks regardless of their F-score with a positive return (percentage numbers)

	F1	F2	F3	F4	F5	F6	F7	F8	F9
1991	86%	97%	21%	90%	24%	26%	9%	29%	32%
1992	85%	95%	53%	88%	34%	44%	25%	54%	47%
1993	84%	96%	50%	87%	35%	43%	23%	55%	57%
1994	91%	95%	49%	85%	28%	34%	14%	47%	38%
1995	89%	94%	49%	81%	37%	43%	20%	49%	40%
1996	90%	95%	55%	84%	35%	44%	25%	49%	43%
1997	89%	95%	49%	85%	41%	42%	29%	59%	44%
1998	85%	95%	42%	83%	47%	37%	24%	51%	60%
1999	93%	97%	48%	87%	44%	41%	19%	51%	52%
2000	90%	94%	47%	83%	38%	46%	13%	43%	40%
2001	81%	95%	39%	88%	42%	52%	19%	35%	56%
2002	81%	94%	55%	89%	39%	48%	19%	52%	66%
2003	87%	94%	54%	88%	30%	56%	15%	48%	47%
2004	92%	95%	62%	85%	23%	47%	22%	52%	38%
2005	91%	95%	55%	87%	31%	43%	19%	41%	32%
2006	94%	95%	54%	79%	35%	51%	15%	51%	44%
2007	84%	96%	43%	86%	45%	43%	10%	42%	51%
2008	79%	95%	36%	84%	53%	55%	9%	41%	34%
2009	80%	98%	40%	94%	30%	60%	12%	55%	77%
2010	92%	97%	64%	87%	31%	46%	9%	62%	43%
2011	90%	95%	53%	83%	39%	43%	6%	41%	36%
2012	87%	96%	42%	87%	39%	45%	8%	50%	57%
Average	**87%**	**95%**	**48%**	**86%**	**36%**	**45%**	**17%**	**48%**	**47%**

In Table 4.8-2 we display results in terms of percentage. It can be highlighted that on average factors that have the highest percentage are F1, F2 and F4, suggesting that it is easy for a company to score in that particular criterion. The same can be noticed when looking at negative returns across the whole sample. Please find the results below.

Table 4.8-3 Criteria relevancy for all stocks regardless of their F-score with a negative return (absolute numbers)

	Total Negative Return Stocks	F1	F2	F3	F4	F5	F6	F7	F8	F9
1991	213	179	196	34	167	50	53	20	50	69
1992	215	191	204	101	176	76	94	57	112	133
1993	222	191	208	126	177	67	100	54	125	113
1994	154	132	129	55	99	38	39	17	41	44
1995	233	188	203	93	162	95	100	59	103	110
1996	108	88	92	43	74	47	47	31	54	57
1997	421	371	393	211	339	202	191	103	219	205
1998	335	298	316	159	272	151	127	85	182	170
1999	207	186	190	104	171	84	85	65	118	108
2000	168	153	153	81	130	53	73	47	70	77
2001	431	336	404	120	378	206	226	79	151	244
2002	28	24	26	19	24	12	19	5	16	15
2003	195	151	174	108	158	53	96	24	94	103
2004	195	164	173	112	159	56	87	34	98	64
2005	160	140	146	94	129	59	69	32	77	58
2006	337	295	315	178	274	128	152	46	177	144
2007	500	451	477	258	429	212	228	54	244	264
2008	45	32	39	19	34	17	25	1	20	12
2009	164	120	154	87	150	49	91	16	89	113
2010	394	333	373	261	326	103	161	41	238	155
2011	208	182	197	100	170	83	87	17	86	93
2012	124	105	117	51	110	47	61	9	69	71

In Table 4.8-3 we show the number of stocks with a negative return that have scored in each F-score criterion. In this table it can be noticed that, for example, only 20 companies out of 213 in 1991 scored in F7; in other words, only 9% of the 213 stocks scored in this criterion.

Table 4.8-4 Criteria relevancy for all stocks regardless of their F-score with a negative return (percentage numbers)

1991	84%	92%	16%	78%	23%	25%	9%	23%	32%
1992	89%	95%	47%	82%	35%	44%	27%	52%	62%
1993	86%	94%	57%	80%	30%	45%	24%	56%	51%
1994	86%	84%	36%	64%	25%	25%	11%	27%	29%
1995	81%	87%	40%	70%	41%	43%	25%	44%	47%
1996	81%	85%	40%	69%	44%	44%	29%	50%	53%
1997	88%	93%	50%	81%	48%	45%	24%	52%	49%
1998	89%	94%	47%	81%	45%	38%	25%	54%	51%
1999	90%	92%	50%	83%	41%	41%	31%	57%	52%
2000	91%	91%	48%	77%	32%	43%	28%	42%	46%
2001	78%	94%	28%	88%	48%	52%	18%	35%	57%
2002	86%	93%	68%	86%	43%	68%	18%	57%	54%
2003	77%	89%	55%	81%	27%	49%	12%	48%	53%
2004	84%	89%	57%	82%	29%	45%	17%	50%	33%
2005	88%	91%	59%	81%	37%	43%	20%	48%	36%
2006	88%	93%	53%	81%	38%	45%	14%	53%	43%
2007	90%	95%	52%	86%	42%	46%	11%	49%	53%
2008	71%	87%	42%	76%	38%	56%	2%	44%	27%
2009	73%	94%	53%	91%	30%	55%	10%	54%	69%
2010	85%	95%	66%	83%	26%	41%	10%	60%	39%
2011	88%	95%	48%	82%	40%	42%	8%	41%	45%
2012	85%	94%	41%	89%	38%	49%	7%	56%	57%
Average	**84%**	**92%**	**48%**	**80%**	**36%**	**45%**	**17%**	**48%**	**47%**

Table 4.8-4 can be interpreted in the same manner as the one displayed above; once again the factors with the highest percentage are F1, F2 and F4.

4.8.2 Portfolios' performances (long portfolios)

In this part we compare our two long portfolios with "Port 1" considered as the long original use of Piotroski F-score (Long 7 to 9) and "Port 4" corresponding to the refinement of the Piotroski F-score where we buy stocks rated with a 6 out of 6.

4.8.2.1 Comparing our two long portfolios while focusing on returns (12-month window)

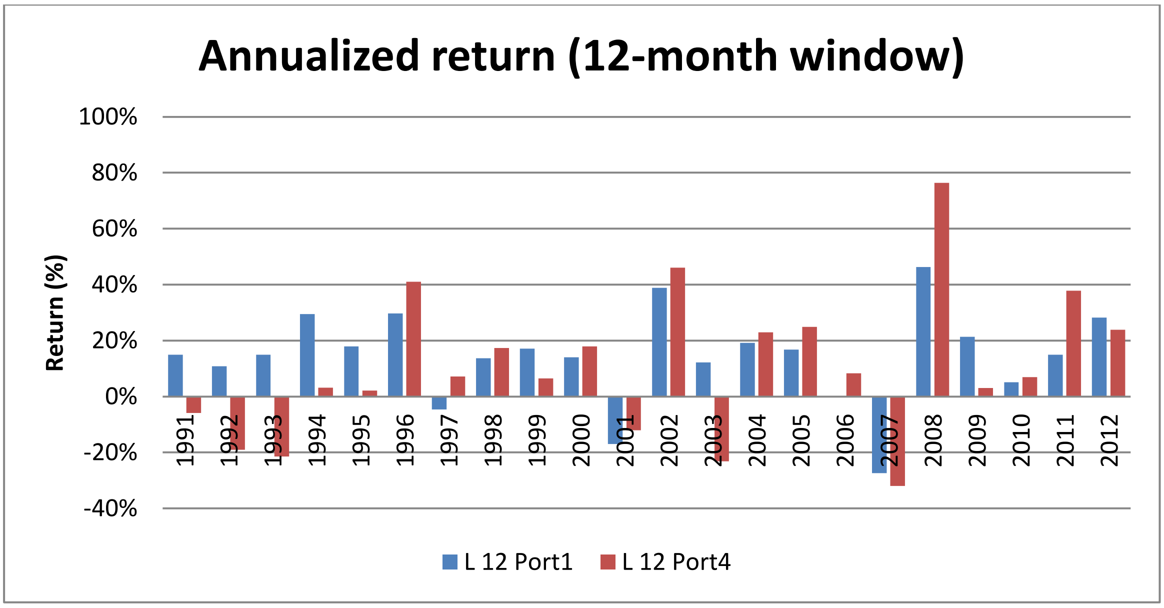

Figure 4.8-1 Long portfolios (12-month window)

In Figure 4.8-1 we display our two long portfolios' annual performance over a 12-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 4". Please refer to the table below for a better understanding of which portfolio is more efficient. In general, it can be noticed that our refinement of Piotroski F-score simulated by "Port 4" shows ability to outperform "Port 1". In fact in 2008, for example, we outperform significantly "Port 1"; however, one caveat could be that on the downside "Port 1" generates less negative return.

Table 4.8-5 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	10
L12 Port4	12	22

>	L 12 Port1	L 12 Port4
L 12 Port1		45%
L12 Port4	55%	

Table 4.8-5 summarizes in terms of absolute and in percentage as a form of a matrix how many times a portfolio generated higher returns than another portfolio. For example, in this case "Portfolio 4" has generated 12 times out of 22 years greater returns than "Portfolio 1"; this corresponds to a percentage of 55%. This suggests that "Portfolio 4" is more efficient at providing investors with higher return on a 12-month basis than "Portfolio 1".

4.8.2.2 Comparing our two long portfolios while focusing on returns (7-month window)

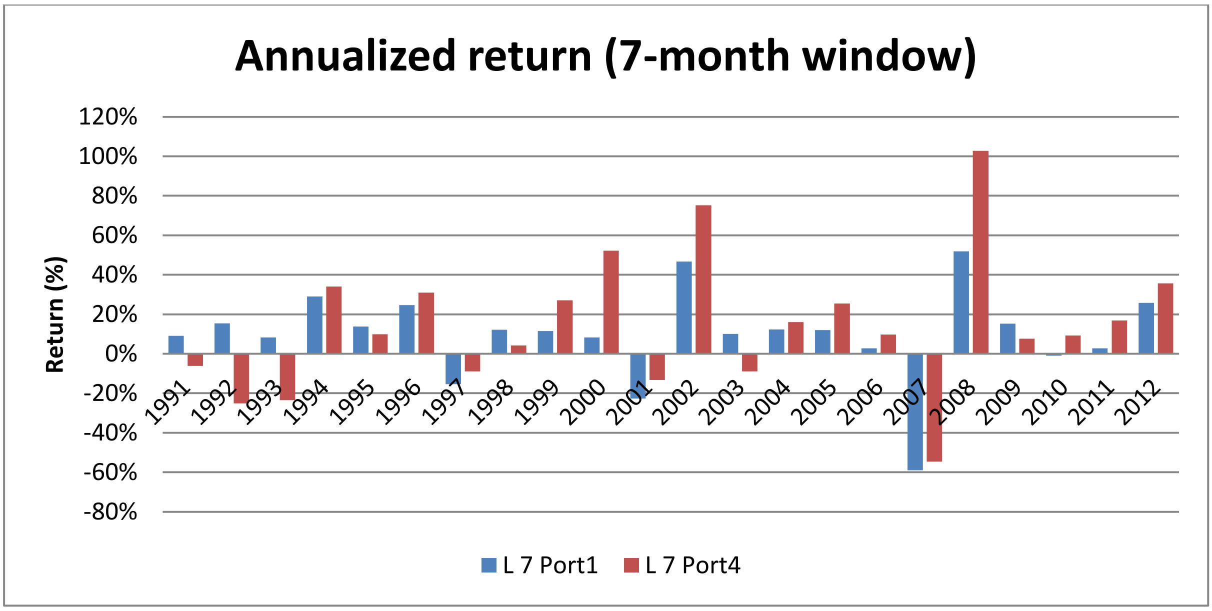

Figure 4.8-2 Long portfolios (7-month window)

In Figure 4.8-2 we display our two long portfolios' annual performance over a 7-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 4". Please refer to the table below for a better understanding of which portfolio is more efficient. In general, it can be noticed that our refinement of Piotroski F-score simulated by "Portfolio 4" shows ability to outperform "Portfolio 1".

Table 4.8-6 Statistical summary L (7-month window)

>	L 7 Port1	L 7 Port4
L 7 Port1	22	7
L7 Port4	15	22

>	L 7 Port1	L 7 Port4
L 7 Port1		32%
L7 Port4	68%	

From Table 4.8-6 it can be seen that "Portfolio 4" outperforms significantly our "Portfolio 1", implying that the refinement strategy of Piotroski F-score is more efficient on a 7-month basis as overall "Portfolio 4" has generated 15 times out 22 greater returns than "Portfolio 1"; this corresponds to a percentage of 68%. This suggests that "Portfolio 4" is more efficient at providing investors with higher return on a 7-month basis than "Portfolio 1".

4.8.2.3 Comparing our two long portfolios while focusing on returns (3-month window)

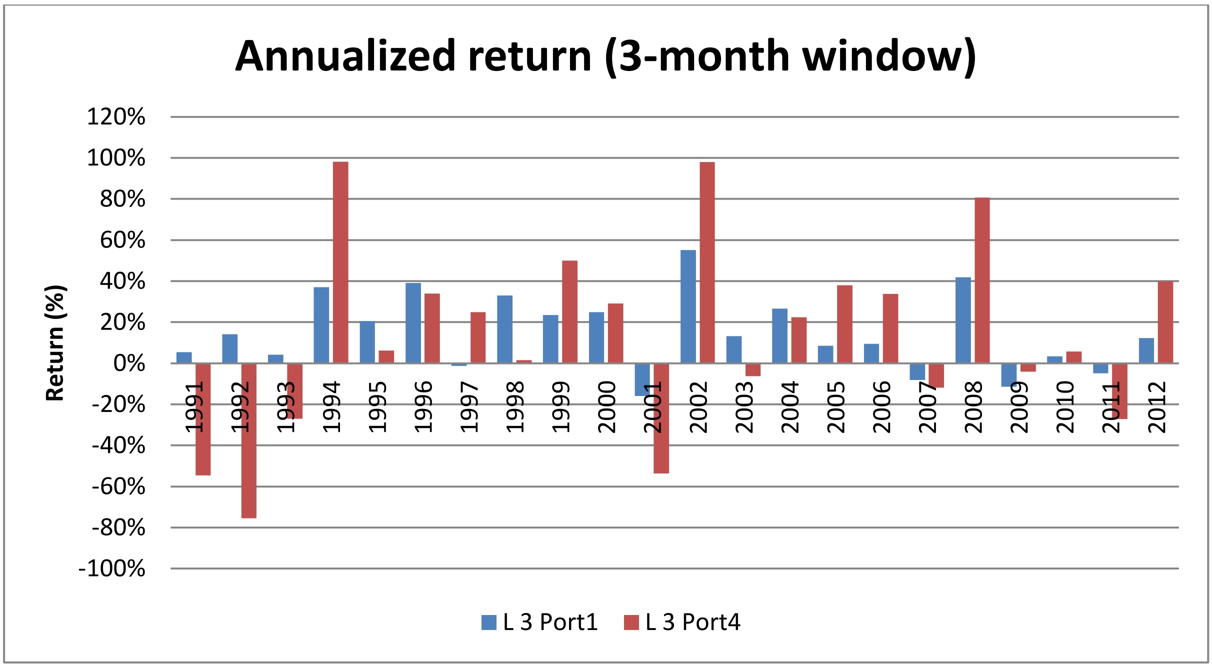

Figure 4.8-3 Long portfolios (3-month window)

In Figure 4.8-3 we display our two long portfolios' annual performance over a 3-month window for each fiscal year over the period 1991 to 2012. Returns are expressed in percentage. The blue bar corresponds to "Portfolio 1", the red bar to "Portfolio 4". Please refer to the table below for a better understanding of which portfolio is more efficient. Overall, both portfolios outperformed each other an equal number of times; however, when "Portfolio 4" outperforms "Portfolio 1" returns are significantly higher.

Table 4.8-7 Statistical summary (3-month window)

>	L 3 Port1	L 3 Port4
L 3 Port1	22	11
L3 Port4	11	22

>	L 3 Port1	L 3 Port4
L 3 Port1		50%
L3 Port4	50%	

From Table 4.8-7 it can be seen that "Portfolio 4" has generated 11 times out 22 greater returns than "Portfolio 1"; this corresponds to a percentage of 50%. This suggests that "Portfolio 4" is not more efficient at providing investors with higher return on a 3-month basis than "Portfolio 1" as both portfolios have the same number of statistical percentages.

4.8.3 Maximum drawdown (long portfolios)

4.8.3.1 Maximum drawdown (12-month window)

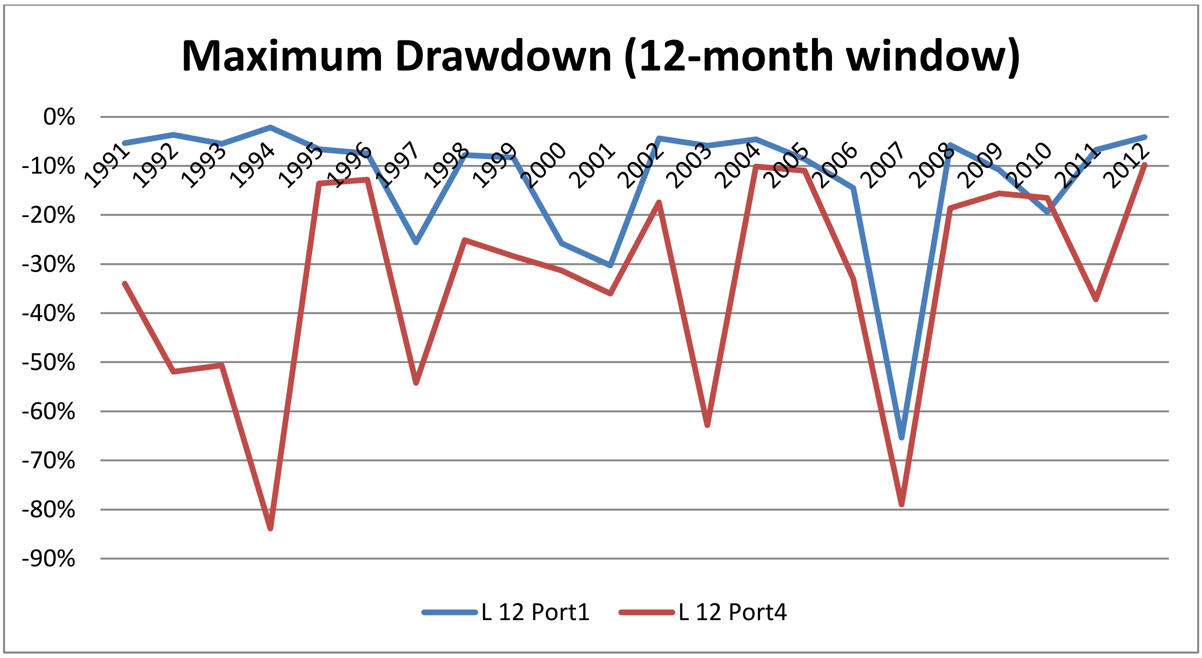

Figure 4.8-4 Maximum drawdown (12-month window)

In this figure, 4.8-4, we present the maximum drawdown of our two portfolios over a 12-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.8-8 Statistical summary L (12-month window)

<	**L 12 Port1**	**L 12 Port4**
L 12 Port1	22	21
L12 Port4	1	22

<	**L 12 Port1**	**L 12 Port4**
L 12 Port1		95%
L12 Port4	5%	

In this table, 4.8-8, "Portfolio 1" has generated 21 times out of 22 years less drawdowns than "Portfolio 4"; this corresponds to a percentage of 95, suggesting that over the year "Portfolio 1" is more efficient at providing investors with less drawdown than "Portfolio 4".

4.8.3.2 Maximum drawdown (7-month window)

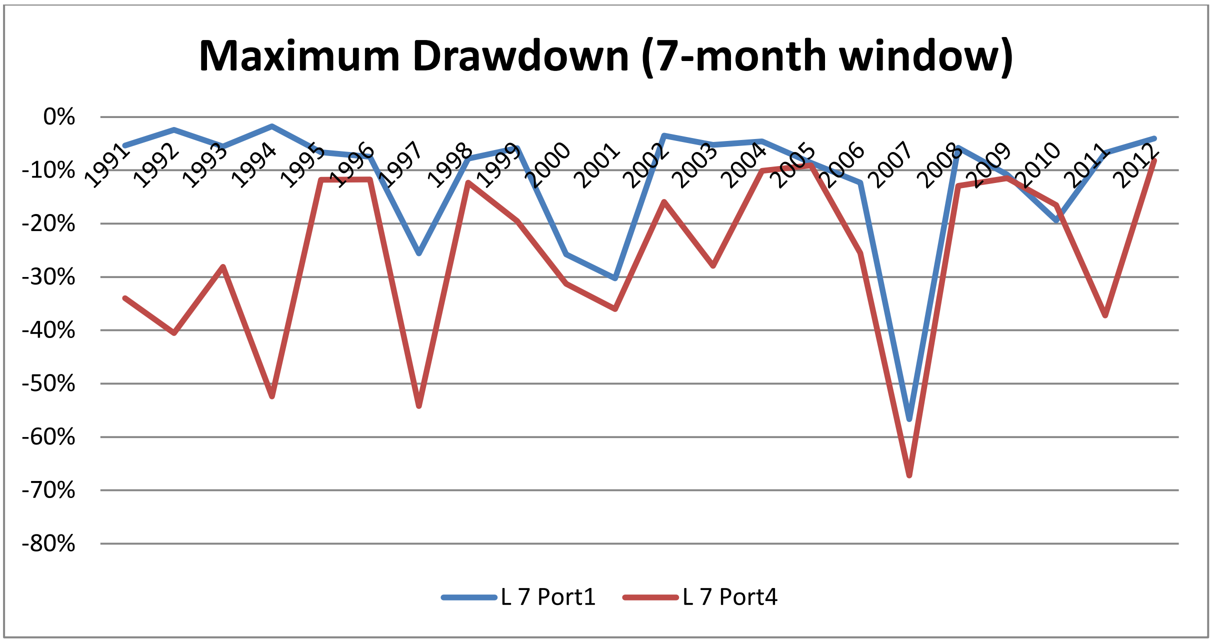

Figure 4.8-5 Maximum drawdown (7-month window)

In this figure, 4.8-5, we present the maximum drawdown of our two portfolios over a 7-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.8-9 Statistical summary L (7-month window)

<	L 7 Port1	L 7 Port4
L 7 Port1	22	21
L7 Port4	1	22

<	L 7 Port1	L 7 Port4
L 7 Port1		95%
L7 Port4	5%	

In this table, 4.8-9, "Portfolio 1" has generated 21 times out of 22 years less drawdowns than "Portfolio 4"; this corresponds to a percentage of 95%, suggesting that over the year "Portfolio 1" is more efficient at providing investors with less drawdown than "Portfolio 4".

4.8.3.3 Maximum drawdown (3-month window)

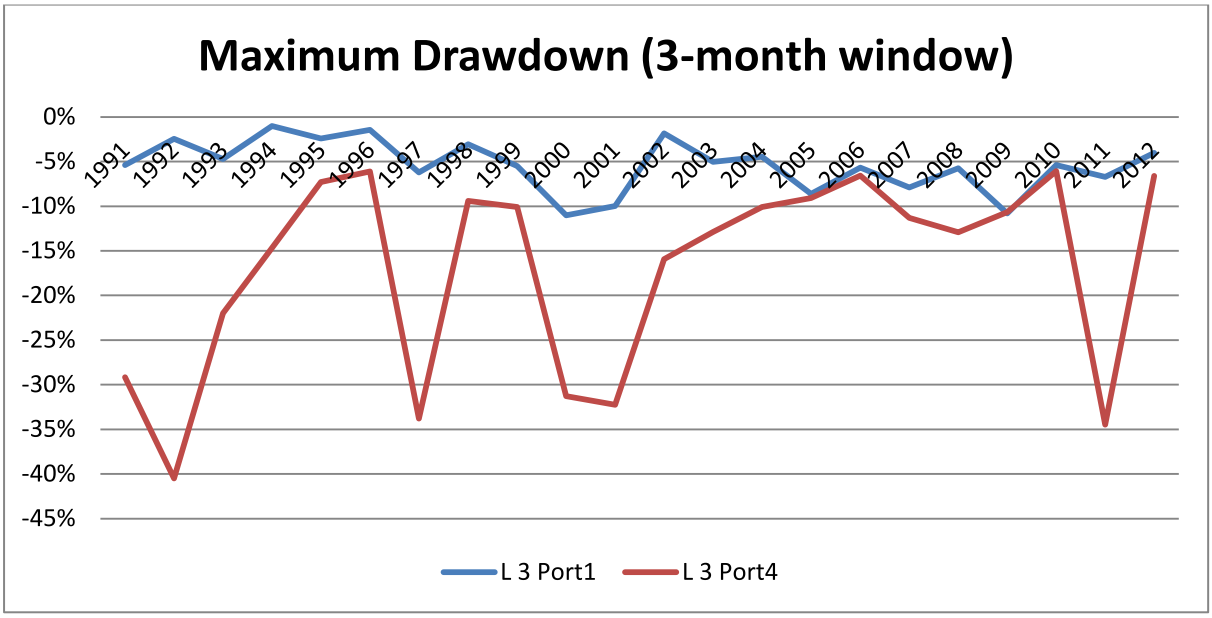

Figure 4.8-6 Maximum drawdown (3-month window)

In this figure, 4.8-5, we present the maximum drawdown of our two portfolios over a 3-month window for the period 1991 to 2012. Please refer to the statistics in the table below for a better understanding of which portfolio has the lowest drawdown.

Table 4.8-10 Statistical summary (3-month window)

<	L 3 Port1	L 3 Port4
L3 Port1	22	21
L3 Port4	1	22

<	L 3 Port1	L 3 Port4
L3 Port1		95%
L3 Port4	5%	

In this table, 4.8-10, “Portfolio 1” has generated 21 times out of 22 years less drawdowns than “Portfolio 4”; this corresponds to a percentage of 95%, suggesting that over the year “Portfolio 1” is more efficient at providing investors with less drawdown than “Portfolio 4”.

4.8.4 Risk-adjusted measures (long portfolios)

4.8.4.1 Sharpe ratio (12-month window)

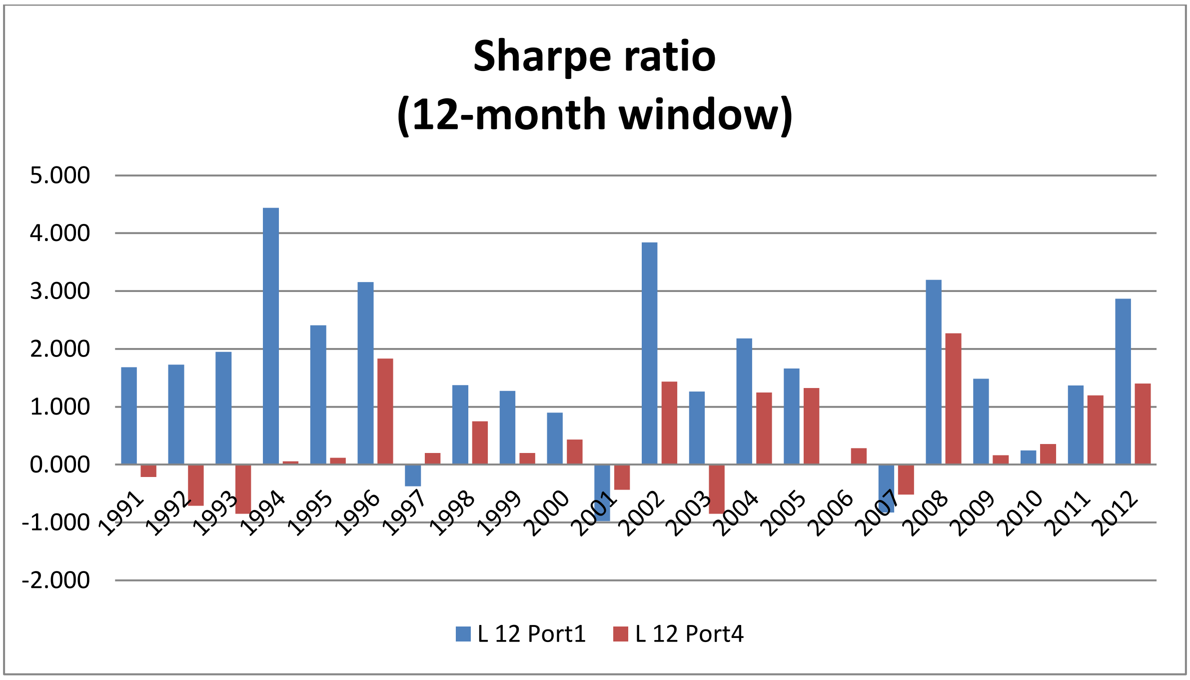

Figure 4.8-7 Sharpe ratio (12-month window)

In this figure, 4.8-7, the Sharpe ratio is used to express how much return is achieved for the amount of risk taken in an investment; when interpreting Sharpe ratio investors look at the highest one as the higher the ratio the better the fund. Once again we try by using some forms of summary statistics to see which portfolio is better at generating higher Sharpe ratios.

Table 4.8-11 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	17
L12 Port4	5	22

>	L 12 Port1	L 12 Port4
L 12 Port1		77%
L12 Port4	23%	

In this table, 4.8-11, "Portfolio 1" has generated 17 times out of 22 years greater Sharpe ratios than "Portfolio 4"; this corresponds to a percentage of 77%, suggesting that "Portfolio 1" is more efficient at providing investors with higher Sharpe ratios on a 12-month basis than "Portfolio 4".

4.8.4.2 Sharpe ratio (7-month window)

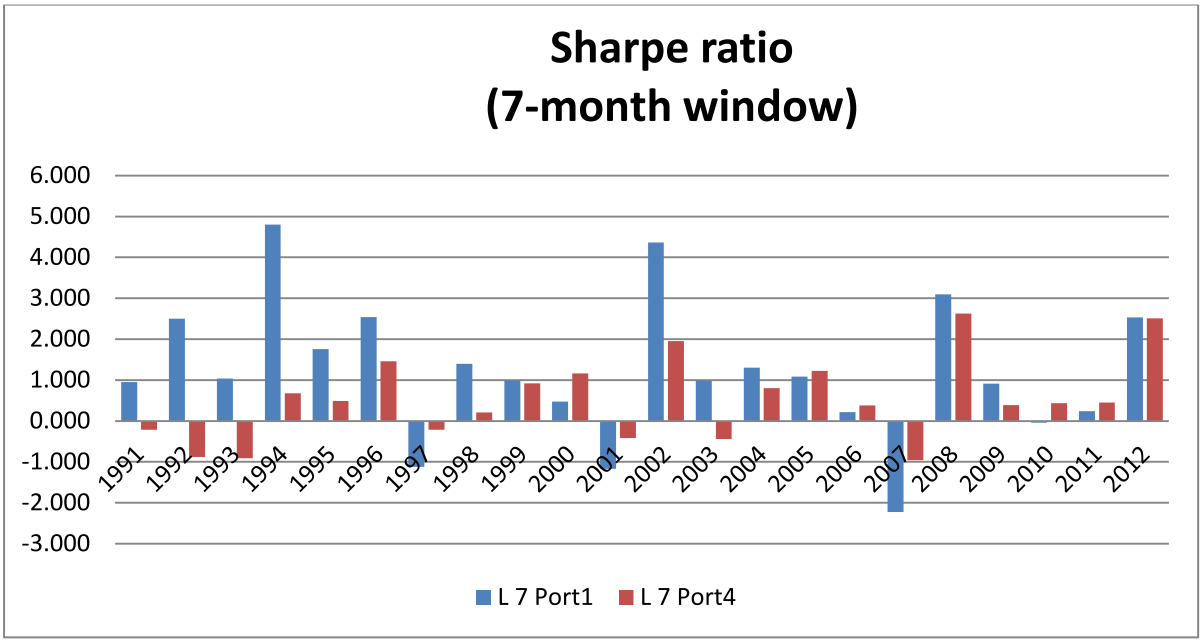

Figure 4.8-8 Sharpe ratio (7-month window)

Table 4.8-12 Statistical summary (7-month window)

>	L 7 Port1	L 7 Port4
L 7 Port1	22	14
L7 Port4	8	22

>	L 7 Port1	L 7 Port4
L 7 Port1		64%
L7 Port4	36%	

In this table, 4.8-12, “Portfolio 1” has generated 14 times out of 22 years greater Sharpe ratios than “Portfolio 4”; this corresponds to a percentage of 64%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Sharpe ratios on a 7-month basis than “Portfolio 4”.

4.8.4.3 Sharpe ratio (3-month window)

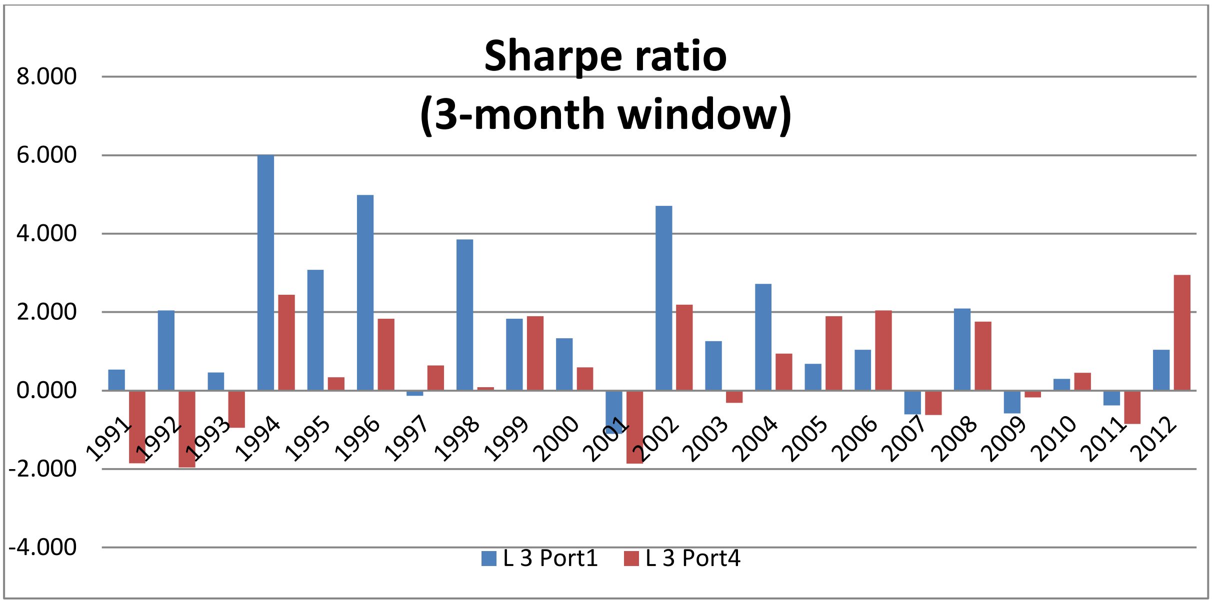

Figure 4.8-9 Sharpe ratio (3-month window)

Table 4.8-13 Statistical summary (3-month window)

>	L 3 Port1	L 3 Port4
L3 Port1	22	15
L3 Port4	7	22

>	L 3 Port1	L 3 Port4
L3 Port1		68%
L3 Port4	32%	

In this table, 4.8-13, “Portfolio 1” has generated 15 times out of 22 years greater Sharpe ratios than “Portfolio 4”; this corresponds to a percentage of 68%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Sharpe ratios on a 7-month basis than “Portfolio 4”.

4.8.4.4 Treynor ratio (12-month window)

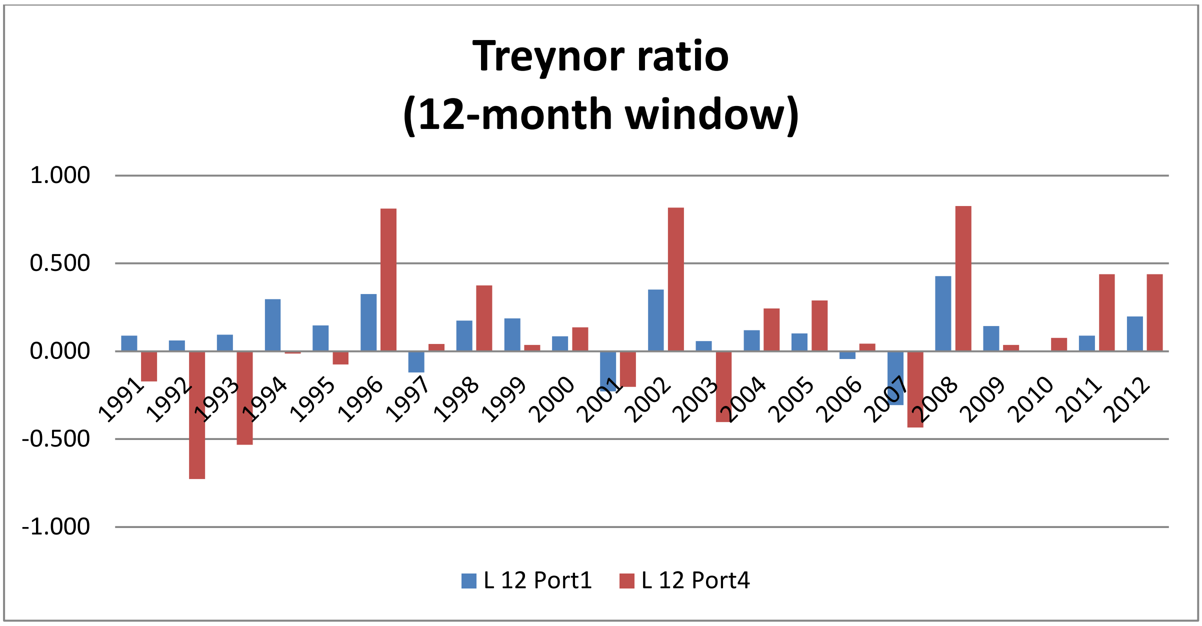

Figure 4.8-10 Treynor ratio (12-month window)

In this figure, 4.8-10, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar returns. Please refer to the table below for comparative purposes between portfolios.

Table 4.8-14 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	9
L12 Port4	13	22

>	L 12 Port1	L 12 Port4
L 12 Port1		41%
L12 Port4	59%	

In this table, 4.8-14, “Portfolio 4” has generated 13 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 59%, suggesting that “Portfolio 4” is more efficient at providing investors with higher Treynor ratios on a 12-month basis than “Portfolio 1”.

4.8.4.5 Treynor ratio (7-month window)

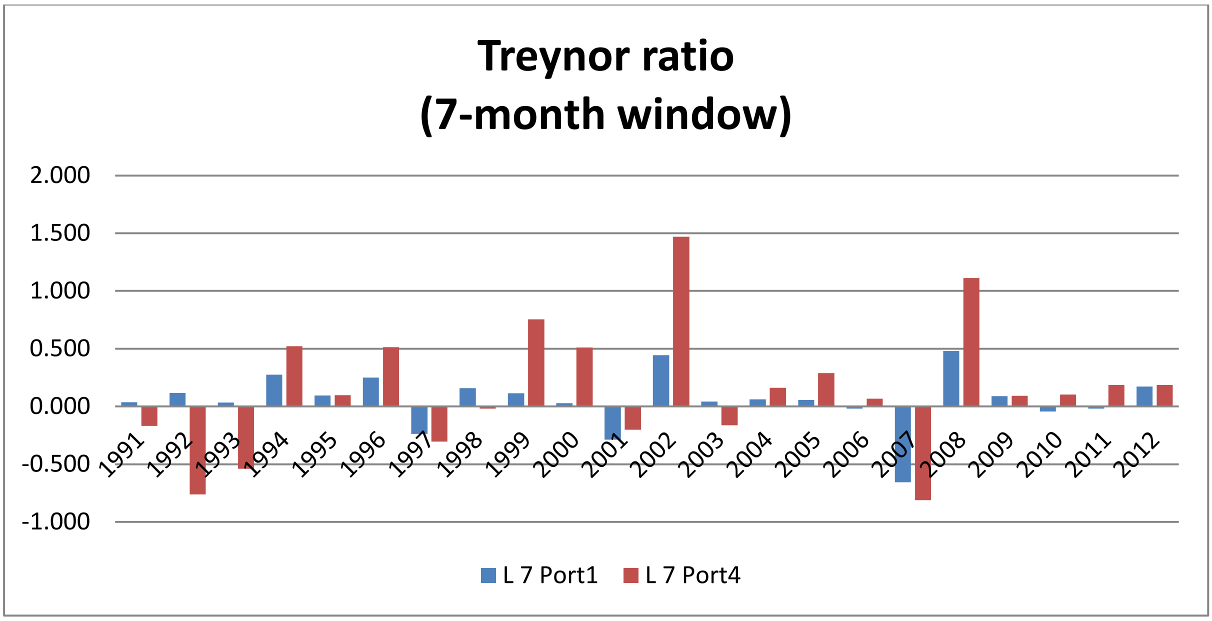

Figure 4.8-11 Treynor ratio (7-month window)

Table 4.8-15 Statistical summary L (7-month window)

>	L 7 Port1	L 7 Port4
L 7 Port1	22	7
L7 Port4	15	22

>	L 7 Port1	L 7 Port4
L 7 Port1		32%
L7 Port4	68%	

In this table, 4.8-15, “Portfolio 4” has generated 15 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 68%, suggesting that “Portfolio 4” is more efficient at providing investors with higher Treynor ratios on a 7-month basis than “Portfolio 1”.

4.8.4.6 Treynor ratio (3-month window)

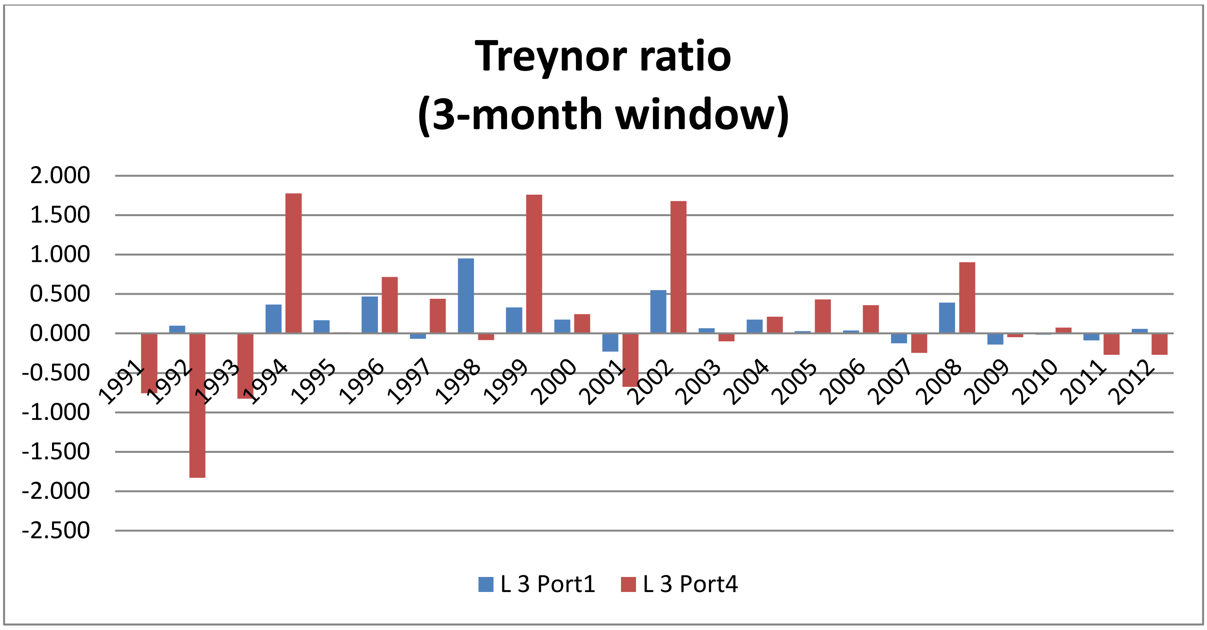

Figure 4.8-12 Treynor ratio (3-month window)

Table 4.8-16 Statistical summary L (3-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	10
L12 Port4	12	22

>	L 3 Port1	L 3 Port4
L3 Port1		45%
L3 Port4	55%	

In this table, 4.8-16, “Portfolio 4” has generated 12 times out of 22 years greater Treynor ratios than “Portfolio 1”; this corresponds to a percentage of 55%, suggesting that “Portfolio 4” is more efficient at providing investors with higher Treynor ratios on a 3-month basis than “Portfolio 1”.

4.8.4.7 Information ratio (12-month window)

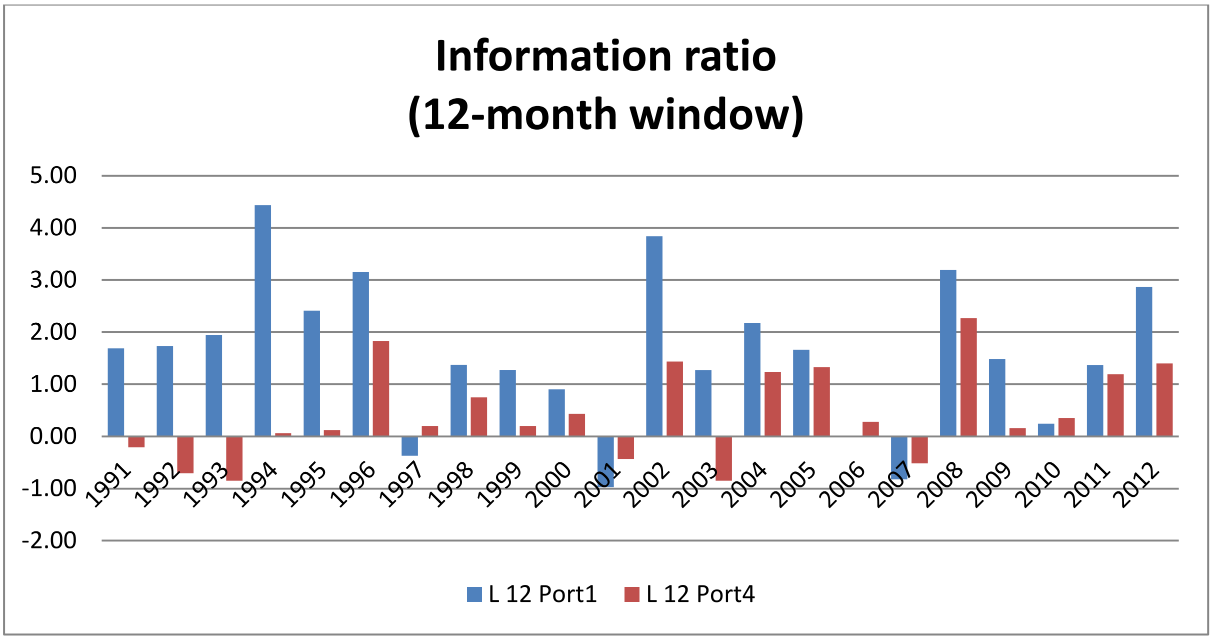

Figure 4.8-13 Information ratio (12-month window)

In this figure, 4.8-13, the Information ratio is used to compare portfolios using the same investment style; the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. Please refer to the table below for comparative purposes between portfolios.

Table 4.8-17 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	17
L12 Port4	5	22

>	L 12 Port1	L 12 Port4
L 12 Port1		77%
L12 Port4	23%	

In this table, 4.8-17, "Portfolio 1" has generated 17 times out of 22 years greater Information ratios than "Portfolio 4"; this corresponds to a percentage of 77%, suggesting that "Portfolio 1" is more efficient at providing investors with higher Information ratios on a 12-month basis than "Portfolio 1".

4.8.4.8 Information ratio (7-month window)

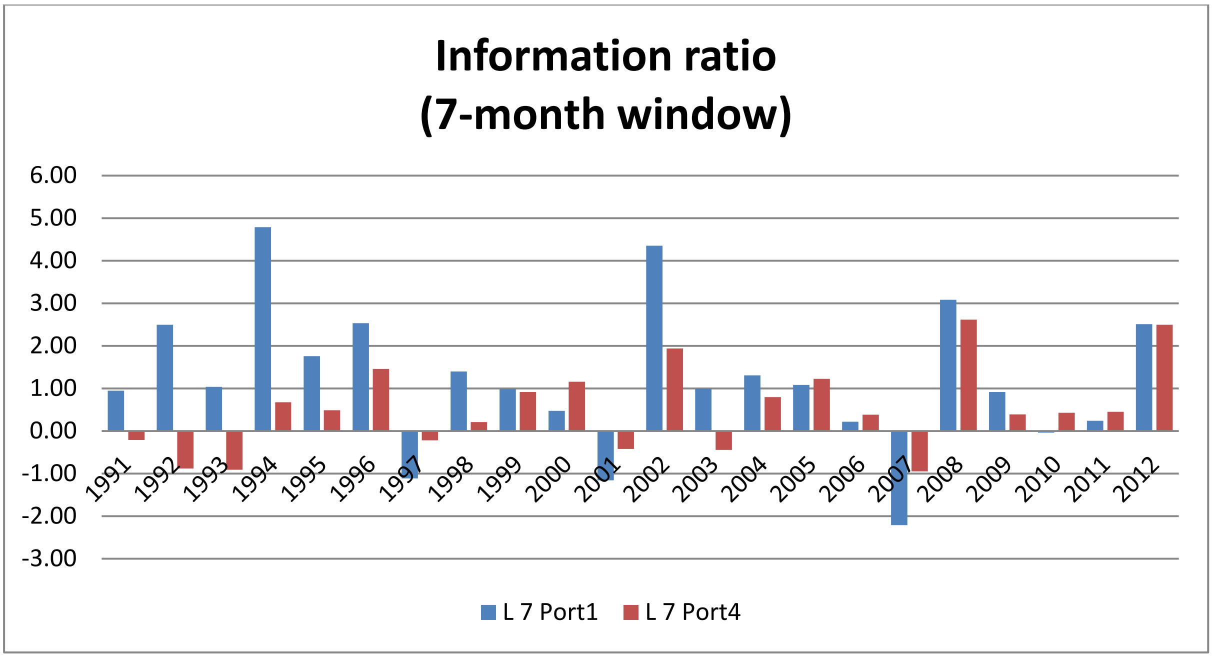

Figure 4.8-14 Information ratio (7-month window)

Table 4.8-18 Statistical summary L (7-month window)

>	L 7 Port1	L 7 Port4
L 7 Port1	22	14
L7 Port4	8	22

>	L 7 Port1	L 7 Port4
L 7 Port1		64%
L7 Port4	36%	

In this table, 4.8-18, "Portfolio 1" has generated 14 times out of 22 years greater Information ratios than "Portfolio 4"; this corresponds to a percentage of 64%, suggesting that "Portfolio 1" is more efficient at providing investors with higher Information ratios on a 7-month basis than "Portfolio 1".

4.8.4.9 Information ratio (3-month window)

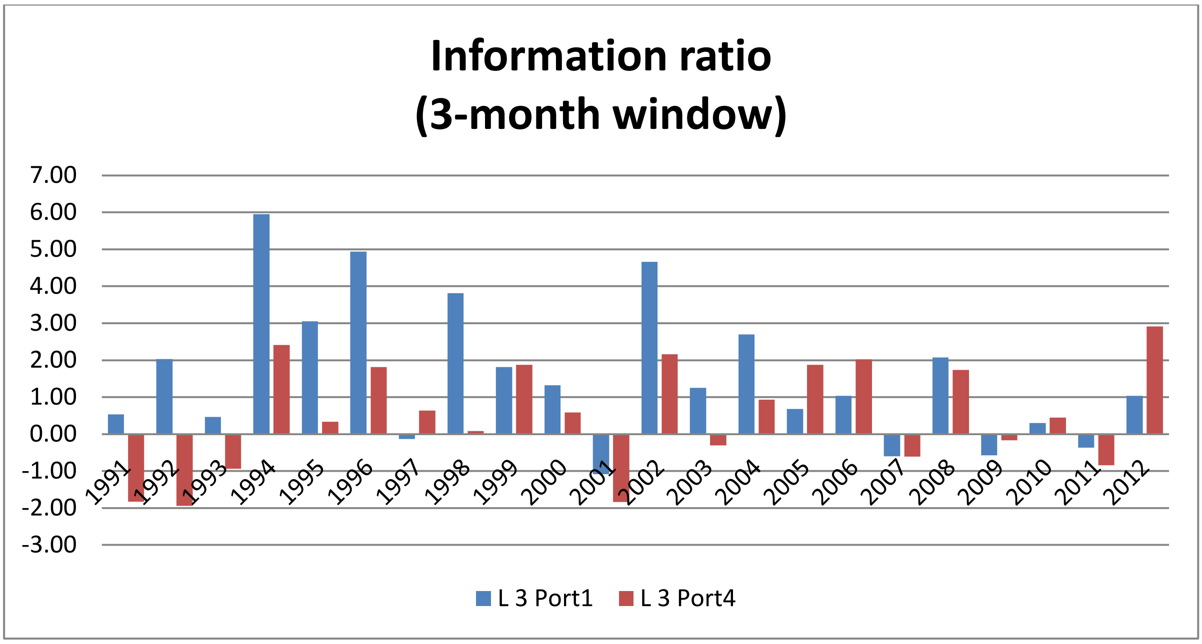

Figure 4.8-15 Information ratio (3-month window)

Table 4.8-19 Statistical summary L (3-month window)

>	**L 12 Port1**	**L 12 Port4**
L 12 Port1	22	15
L12 Port4	7	22

>	**L 3 Port1**	**L 3 Port4**
L3 Port1		68%
L3 Port4	32%	

In this table, 4.8-19, “Portfolio 1” has generated 15 times out of 22 years greater Information ratios than “Portfolio 4”; this corresponds to a percentage of 68%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Information ratios on a 3-month basis than “Portfolio 1”.

4.8.4.10 Sortino ratio (12-month window)

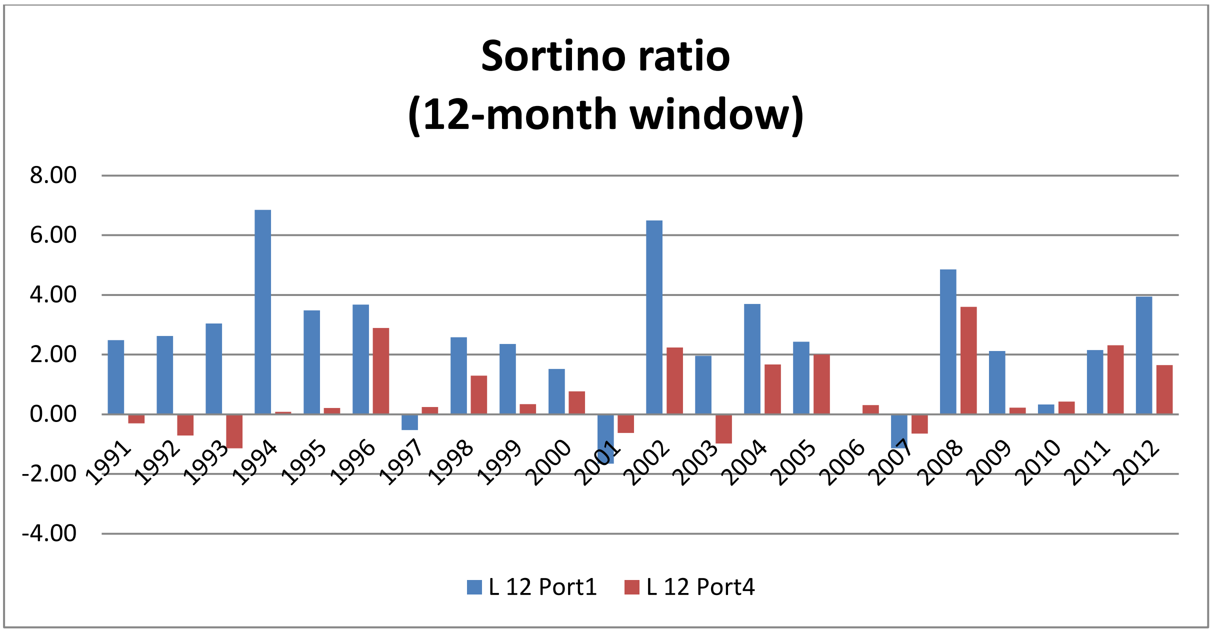

Figure 4.8-16 Sortino ratio (12-month window)

In this figure, 4.8-16, the Sortino ratio, which replaces the volatility in the Sharpe ratio with a measure of downside deviations, is used to evaluate which portfolio is better at generating higher Sortino ratio. Please refer to the table below for comparative purposes.

Table 4.8-20 Statistical summary L (12-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	16
L12 Port4	6	22

>	L 12 Port1	L 12 Port4
L 12 Port1		73%
L12 Port4	27%	

In this table, 4.8-20, “Portfolio 1” has generated 16 times out of 22 years greater Sortino ratios than “Portfolio 4”; this corresponds to a percentage of 73%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios on a 12-month basis than “Portfolio 1”.

4.8.4.11 Sortino ratio (7-month window)

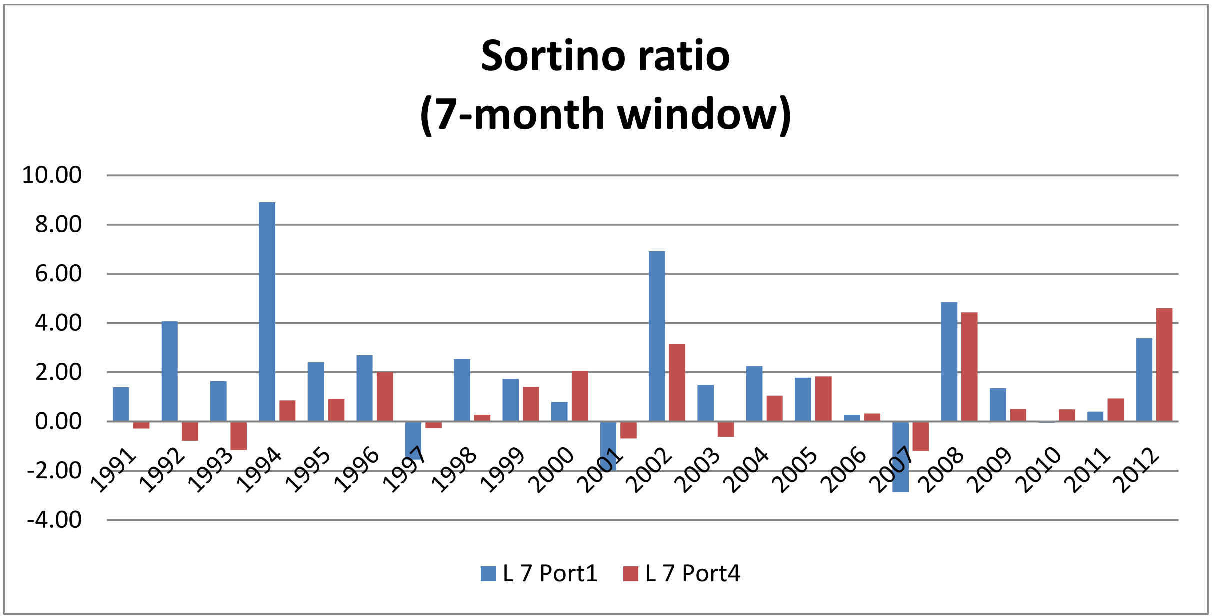

Figure 4.8-17 Sortino ratio (7-month window)

Table 4.8-21 Statistical summary L (7-month window)

>	L 7 Port1	L 7 Port4
L 7 Port1	22	13
L7 Port4	9	22

>	L 7 Port1	L 7 Port4
L 7 Port1		59%
L7 Port4	41%	

In this table, 4.8-21, “Portfolio 1” has generated 13 times out of 22 years greater Sortino ratios than “Portfolio 4”; this corresponds to a percentage of 59%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios on a 7-month basis than “Portfolio 1”.

4.8.4.12 Sortino ratio (3-month window)

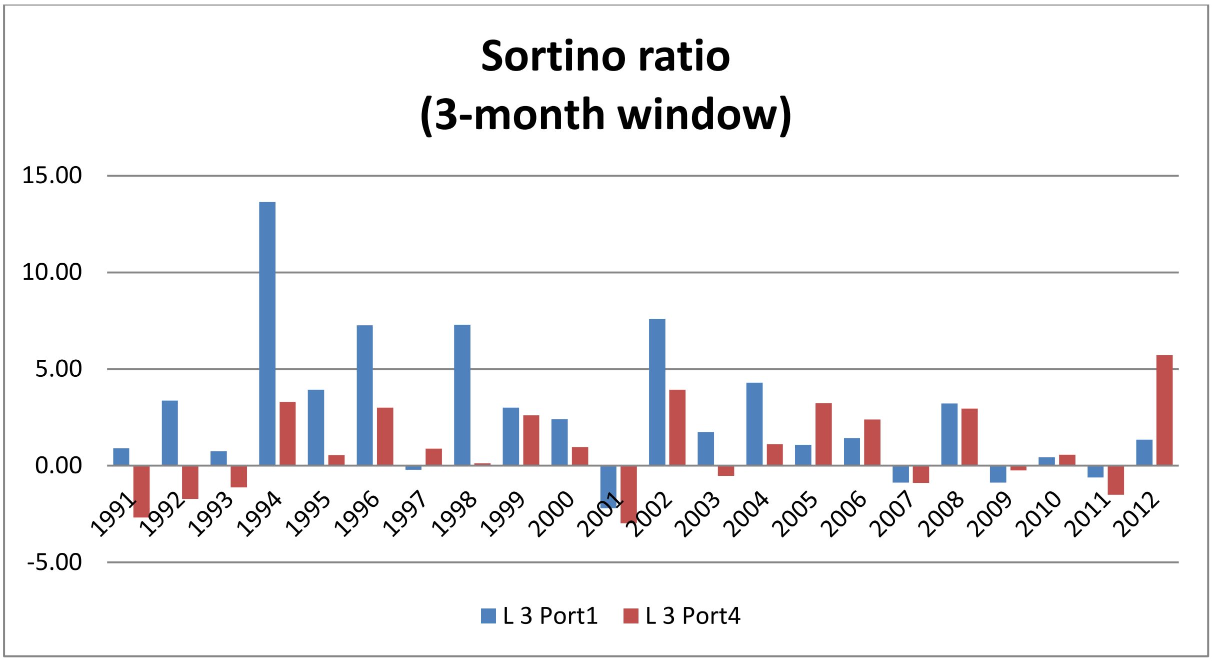

Figure 4.8-18 Sortino ratio (3-month window)

Table 4.8-22 Statistical summary L (3-month window)

>	L 12 Port1	L 12 Port4
L 12 Port1	22	16
L12 Port4	6	22

>	L 3 Port1	L 3 Port4
L3 Port1		73%
L3 Port4	27%	

In this table, 4.8-22, “Portfolio 1” has generated 16 times out of 22 years greater Sortino ratios than “Portfolio 4”; this corresponds to a percentage of 73%, suggesting that “Portfolio 1” is more efficient at providing investors with higher Sortino ratios on a 3-month basis than “Portfolio 1”.

4.9 Conclusion

This chapter has examined the impact of the F-score on a long-short portfolio. Consistent with the literature, this chapter found that distinguishing between winners and losers can help an investor to shift the distribution return of his portfolio.

The main goal of this chapter was to develop a market neutral approach to our Piotroski F-score by assessing results as we were looking for third parties to invest in our strategy. Using daily data from 1991 to 2012 we examined whether our portfolio was able to deliver subsequent return to investors.

This portfolio was then back tested using different risk metrics used in the industry over the period 1991 to 2012; in order to do so we applied some risk-adjusted return measures. Our strategy has not been tested using transaction costs; however, we believe that, due to the high performance, this will not affect the strategy while producing positive returns.

Furthermore, we are improving the research by dealing with the data-snooping bias by constructing some refinement of the Piotroski F-score where we consider that variables can be dropped to constitute a new sort of F-score and create on this basis portfolios where we compare results in terms of returns, drawdown and risk-adjusted measures, as is often the case in the industry.

Finally, we highly believe the strategy can be used in the current environment and can help investors to increase their wealth.

4.10 Appendices

4.10.1 Appendix A

In Table 4.10-1 below we show the different returns expressed as a percentage earned by portfolios for the three frequencies' periods.

Table 4.10-1 Displays returns for the different time horizons on the long portfolio, the short portfolio, the market, the long-short portfolio and the excess return

	PORT L 12	PORT L 7	PORT L 3	PORT S 12	PORT S 7	PORT S 3	PORT L/S 12	PORT L/S 7	PORT L/S 3	MARK 12	MARK 7	MARK 3	Excess Return 12	Excess Return 7	Excess Return 3
1991	14.98%	9.02%	5.34%	-14.09%	-5.36%	7.63%	29.07%	14.38%	-2.29%	11.48%	6.05%	-0.15%	17.59%	8.33%	-2.14%
1992	10.86%	15.44%	14.19%	-23.27%	-26.52%	-12.44%	34.13%	41.97%	26.63%	7.33%	9.92%	11.60%	26.81%	32.04%	15.02%
1993	14.95%	8.36%	4.19%	-9.51%	-6.15%	-3.57%	24.46%	14.51%	7.76%	10.76%	4.99%	1.84%	13.70%	9.51%	5.93%
1994	29.43%	29.08%	37.01%	-27.03%	-23.79%	-38.34%	56.46%	52.86%	75.35%	27.32%	28.16%	31.56%	29.14%	24.70%	43.79%
1995	17.89%	13.77%	20.54%	-21.14%	-13.26%	-16.12%	39.02%	27.03%	36.66%	20.57%	16.10%	18.01%	18.45%	10.94%	18.65%
1996	29.73%	24.58%	39.01%	-31.38%	-32.60%	-36.70%	61.10%	57.18%	75.71%	33.56%	26.59%	41.74%	27.55%	30.58%	33.97%
1997	-4.66%	-15.33%	-1.25%	4.29%	22.23%	2.76%	-8.94%	-37.56%	-4.01%	12.91%	1.09%	7.30%	-21.85%	-38.66%	-11.31%
1998	13.66%	12.14%	33.04%	-31.19%	-27.77%	-53.41%	44.84%	39.92%	86.45%	24.63%	19.92%	30.98%	20.22%	19.99%	55.47%
1999	17.15%	11.53%	23.51%	-21.53%	-12.44%	-16.53%	38.68%	23.97%	40.04%	-15.68%	-9.91%	0.17%	54.37%	33.88%	39.87%
2000	14.08%	8.21%	24.92%	-22.40%	-15.87%	-37.90%	36.48%	24.08%	62.82%	-6.71%	-12.92%	2.70%	43.20%	37.00%	60.12%
2001	-16.97%	-22.72%	-16.01%	13.59%	25.89%	9.34%	-30.56%	-48.61%	-25.34%	-15.64%	-23.69%	-28.00%	-14.92%	-24.92%	2.66%
2002	38.84%	46.62%	55.10%	-54.69%	-67.80%	-86.11%	93.53%	114.41%	141.21%	29.52%	35.60%	44.04%	64.00%	78.81%	97.16%
2003	12.20%	10.06%	13.18%	-13.74%	-9.48%	-15.08%	25.94%	19.54%	28.26%	8.97%	7.59%	9.66%	16.97%	11.95%	18.60%
2004	19.18%	12.29%	26.60%	-13.55%	-8.33%	-26.19%	32.73%	20.63%	52.79%	15.34%	10.24%	18.62%	17.39%	10.39%	34.17%
2005	16.80%	12.01%	8.45%	-13.93%	-9.98%	-10.87%	30.73%	22.00%	19.31%	15.23%	12.14%	3.46%	15.50%	9.86%	15.86%
2006	0.08%	2.71%	9.47%	17.77%	17.34%	-5.99%	-17.69%	-14.63%	15.46%	3.22%	13.03%	16.92%	-20.91%	-27.66%	-1.46%
2007	-27.40%	-58.97%	-8.18%	27.41%	75.86%	30.19%	-54.81%	-134.83%	-38.37%	-38.11%	-68.48%	-17.41%	-16.70%	-66.35%	-20.96%
2008	46.34%	51.84%	41.81%	-63.15%	-75.72%	-80.51%	109.49%	127.56%	122.32%	37.34%	41.20%	32.38%	72.15%	86.36%	89.94%
2009	21.32%	15.30%	-11.46%	-13.68%	-8.94%	4.08%	35.01%	24.24%	-15.54%	14.97%	10.78%	-14.37%	20.04%	13.46%	-1.16%
2010	5.14%	-0.91%	3.35%	3.11%	5.42%	0.51%	2.03%	-6.33%	2.83%	5.01%	2.16%	2.37%	-2.98%	-8.49%	0.46%
2011	14.94%	2.79%	-4.82%	-29.72%	-13.63%	-5.48%	44.66%	16.41%	0.66%	16.65%	9.31%	1.72%	28.01%	7.10%	-1.06%
2012	28.25%	25.83%	12.32%	-27.77%	-25.12%	-19.21%	56.02%	50.96%	31.53%	23.14%	21.03%	11.72%	32.89%	29.92%	19.81%

4.10.2 Appendix B

In Table 4.10-2 below we present the different maximum drawdown known by our portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-2 Displays the maximum drawdown numbers for the different time horizons on the long-short portfolio and the market

Maximum Drawdown	POR L/S 12	POR L/S 7	POR L/S 3	MARK 12	MARK 7	MARK 3
1991	-9.13%	-9.13%	-9.13%	-3.72%	-3.72%	-3.73%
1992	-6.12%	-5.08%	-3.87%	-2.74%	-2.53%	-2.52%
1993	-12.98%	-10.79%	-7.97%	-4.24%	-4.24%	-3.61%
1994	-6.13%	-6.13%	-2.32%	-2.63%	-1.87%	-1.34%
1995	-12.89%	-12.89%	-6.57%	-5.79%	-5.79%	-3.08%
1996	-13.96%	-13.96%	-3.16%	-8.82%	-8.82%	-2.28%
1997	-62.12%	-62.12%	-13.22%	-15.05%	-15.05%	-4.13%
1998	-11.12%	-11.12%	-5.65%	-6.62%	-6.62%	-3.99%
1999	-15.83%	-14.74%	-12.56%	-28.85%	-13.17%	-10.77%
2000	-41.46%	-41.46%	-14.34%	-28.16%	-28.16%	-7.81%
2001	-67.94%	-67.94%	-21.78%	-29.18%	-29.18%	-12.68%
2002	-10.16%	-10.00%	-6.66%	-4.68%	-3.31%	-2.30%
2003	-11.87%	-11.87%	-10.96%	-4.25%	-4.25%	-3.68%
2004	-12.25%	-12.25%	-8.91%	-3.53%	-3.53%	-3.31%
2005	-12.75%	-12.75%	-12.75%	-5.55%	-5.55%	-5.55%
2006	-54.49%	-30.05%	-10.42%	-13.26%	-6.67%	-3.01%
2007	-143.94%	-128.60%	-22.44%	-73.68%	-62.28%	-9.95%
2008	-13.60%	-13.60%	-12.29%	-6.21%	-5.81%	-5.81%
2009	-22.10%	-22.10%	-22.10%	-9.94%	-9.94%	-9.91%
2010	-41.26%	-41.26%	-12.72%	-14.58%	-14.58%	-5.06%
2011	-10.46%	-10.46%	-10.46%	-5.27%	-5.27%	-5.27%
2012	-6.87%	-6.87%	-6.87%	-3.78%	-3.78%	-3.78%

4.10.3 Appendix C

In Table 4.10-3 below we present the different beta generated by our portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-3 Displays the beta numbers for the different time horizons on the long portfolio, the short portfolio and the long-short portfolio

Beta	PORT L12	PORT L7	PORT L3	PORT S12	PORT S7	PORT S3	POR L/S 12	POR L/S 7	POR L/S 3
1991	1.13	1.11	1.09	-0.98	-1.02	-1.02	-0.14	-0.09	-0.07
1992	0.96	0.90	0.92	-1.17	-1.15	-1.15	0.21	0.25	0.23
1993	1.05	1.03	1.03	-1.07	-1.12	-1.17	0.02	0.09	0.14
1994	0.82	0.88	0.87	-0.86	-0.93	-0.78	0.04	0.05	-0.09
1995	0.87	0.93	0.92	-0.82	-0.89	-0.96	-0.05	-0.04	0.04
1996	0.76	0.78	0.72	-0.84	-0.81	-0.71	0.08	0.03	-0.02
1997	0.81	0.85	0.91	-0.95	-1.04	-0.91	0.14	0.19	0.00
1998	0.49	0.45	0.29	-0.61	-0.53	-0.41	0.12	0.08	0.12
1999	0.65	0.57	0.56	-0.77	-0.73	-0.68	0.12	0.16	0.13
2000	1.07	1.09	1.13	-0.90	-0.90	-0.83	-0.17	-0.19	-0.29
2001	0.96	0.97	0.91	-1.01	-1.01	-0.98	0.05	0.04	0.07
2002	0.97	0.93	0.91	-1.48	-1.45	-1.44	0.52	0.51	0.53
2003	1.24	1.24	1.23	-1.37	-1.41	-1.40	0.13	0.17	0.17
2004	1.19	1.21	1.24	-1.29	-1.29	-1.31	0.10	0.08	0.07
2005	1.16	1.24	1.22	-1.17	-1.19	-1.13	0.01	-0.04	-0.09
2006	1.11	1.16	1.18	-1.23	-1.12	-1.15	0.11	-0.04	-0.02
2007	1.06	0.97	1.07	-1.34	-1.27	-1.35	0.28	0.30	0.28
2008	0.97	0.98	0.94	-1.46	-1.52	-1.55	0.50	0.55	0.60
2009	1.13	1.16	1.17	-1.30	-1.29	-1.23	0.17	0.12	0.06
2010	1.32	1.31	1.10	-1.23	-1.22	-1.19	-0.09	-0.10	0.09
2011	1.13	1.11	1.13	-1.18	-1.20	-1.28	0.05	0.09	0.15
2012	1.18	1.20	1.24	-1.15	-1.13	-1.13	-0.03	-0.07	-0.10

4.10.4 Appendix D

In Table 4.10-4 below we present the different ratios used to measure risks and the volatility known by our portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-4 Displays the different ratios used to measure risks and the volatility across the different time horizons on the long-short portfolio

	L/S 12 Sharpe Ratio	L/S 7 Sharpe Ratio	L/S 3 Sharpe Ratio	L/S 12 IR	L/S 7 IR	L/S 3 IR	L/S 12 Sortino Ratio	L/S 7 Sortino Ratio	L/S 3 Sortino Ratio	L/S 12 Treynor Ratio	L/S 7 Treynor Ratio	L/S 3 Treynor Ratio	L/S Vol 12	L/S Vol 7	L/S Vol 3
1991	1.965	0.910	-0.138	1.963	0.909	-0.133	2.892	1.403	-0.208	0.114	0.044	-0.035	14.77%	15.76%	16.98%
1992	2.501	3.077	1.905	2.497	3.066	1.888	3.705	4.734	2.736	0.137	0.180	0.104	13.63%	13.62%	13.95%
1993	1.679	0.947	0.448	1.678	0.946	0.446	2.491	1.364	0.641	0.092	0.044	0.013	14.54%	15.26%	17.22%
1994	4.522	4.588	6.696	4.514	4.570	6.627	5.612	6.382	10.687	0.305	0.265	0.412	12.47%	11.51%	10.83%
1995	2.841	1.888	2.764	2.837	1.882	2.737	3.878	2.401	3.510	0.201	0.121	0.169	13.72%	14.29%	13.24%
1996	3.223	2.960	4.958	3.216	2.949	4.907	3.473	2.810	6.803	0.350	0.329	0.494	18.94%	19.30%	15.26%
1997	-0.330	-1.238	-0.219	-0.327	-1.231	-0.214	-0.462	-1.669	-0.332	-0.080	-0.224	-0.050	27.24%	30.38%	18.56%
1998	2.375	2.456	5.511	2.371	2.447	5.454	4.271	4.524	9.990	0.360	0.356	1.154	18.86%	16.24%	15.68%
1999	1.392	0.945	1.428	1.390	0.943	1.414	2.381	1.518	2.139	0.237	0.145	0.281	27.75%	25.31%	27.99%
2000	1.288	0.771	1.923	1.286	0.769	1.904	2.168	1.278	3.394	0.159	0.096	0.295	28.30%	31.15%	32.64%
2001	-0.868	-1.244	-0.874	-0.864	-1.237	-0.863	-1.479	-2.118	-1.707	-0.180	-0.272	-0.161	35.25%	39.12%	29.05%
2002	3.586	4.117	4.561	3.578	4.099	4.512	5.642	6.148	6.649	0.361	0.460	0.579	26.07%	27.78%	30.95%
2003	1.284	0.908	1.286	1.283	0.906	1.275	1.915	1.307	1.697	0.080	0.055	0.089	20.17%	21.47%	21.93%
2004	1.797	1.074	2.646	1.795	1.072	2.619	2.979	1.767	4.386	0.112	0.063	0.188	18.19%	19.15%	19.93%
2005	1.564	1.045	0.835	1.563	1.043	0.828	2.238	1.761	1.366	0.110	0.070	0.061	19.61%	20.99%	23.06%
2006	-0.577	-0.611	0.874	-0.574	-0.604	0.867	-0.824	-0.805	1.251	-0.097	-0.086	0.045	30.74%	24.01%	17.64%
2007	-0.739	-2.234	-1.304	-0.736	-2.223	-1.288	-1.046	-3.041	-2.098	-0.250	-0.622	-0.180	74.25%	60.37%	29.45%
2008	3.130	3.108	2.427	3.123	3.094	2.401	4.502	4.758	3.702	0.430	0.490	0.471	34.97%	41.03%	50.39%
2009	1.133	0.684	-0.384	1.132	0.682	-0.379	1.687	1.058	-0.575	0.123	0.079	-0.085	30.85%	35.38%	40.55%
2010	0.049	-0.144	0.127	0.050	-0.142	0.128	0.066	-0.178	0.193	-0.012	-0.045	-0.009	40.13%	44.44%	21.94%
2011	2.021	0.696	0.022	2.017	0.694	0.024	3.202	1.126	0.036	0.172	0.049	-0.018	22.08%	23.53%	27.45%
2012	2.906	2.556	1.388	2.901	2.534	1.374	4.166	3.500	1.813	0.219	0.197	0.112	19.26%	19.92%	22.69%
Max	4.522	4.588	6.696	4.514	4.570	6.627	5.642	6.382	10.687	0.430	0.490	1.154	74.25%	60.37%	50.39%
Min	-0.868	-2.234	-1.304	-0.864	-2.223	-1.288	-1.479	-3.041	-2.098	-0.250	-0.622	-0.180	12.47%	11.51%	10.83%
mean	1.670	1.239	1.676	1.668	1.235	1.660	2.430	1.819	2.549	0.134	0.082	0.179	25.54%	25.91%	23.52%
median	1.738	0.946	1.337	1.736	0.944	1.324	2.692	1.461	1.755	0.130	0.074	0.096	21.13%	22.50%	21.94%

4.10.5 Appendix E

In Table 4.10-5 below we present the correlation measured across by our portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-5 Displays the correlation measured across the different time horizons on the long portfolio, short portfolio and the long-short portfolio

	PORT L12	PORT L7	PORT L3	PORT S12	PORT S7	PORT S3	POR L/S 12	POR L/S 7	POR L/S 3
1991	0.80	0.79	0.81	-0.84	-0.86	-0.86	0.04	0.05	0.05
1992	0.78	0.74	0.74	-0.65	-0.61	-0.70	-0.13	-0.09	-0.04
1993	0.83	0.83	0.84	-0.76	-0.81	-0.86	-0.07	-0.07	0.02
1994	0.78	0.78	0.78	-0.76	-0.75	-0.68	-0.02	-0.02	-0.09
1995	0.83	0.84	0.86	-0.79	-0.83	-0.80	-0.04	-0.05	-0.06
1996	0.87	0.90	0.87	-0.84	-0.85	-0.80	-0.03	-0.06	-0.07
1997	0.88	0.91	0.87	-0.82	-0.87	-0.80	-0.06	-0.10	-0.07
1998	0.61	0.58	0.39	-0.69	-0.64	-0.52	0.08	0.11	0.13
1999	0.79	0.77	0.82	-0.78	-0.75	-0.77	-0.01	0.01	-0.05
2000	0.90	0.91	0.93	-0.85	-0.85	-0.84	-0.05	-0.06	-0.09
2001	0.93	0.93	0.86	-0.89	-0.90	-0.86	-0.03	-0.03	-0.01
2002	0.92	0.92	0.93	-0.83	-0.83	-0.83	-0.09	-0.09	-0.09
2003	0.92	0.92	0.93	-0.85	-0.87	-0.90	-0.07	-0.07	-0.02
2004	0.92	0.92	0.93	-0.83	-0.86	-0.87	-0.08	-0.09	-0.06
2005	0.91	0.92	0.93	-0.90	-0.91	-0.92	-0.02	-0.02	-0.01
2006	0.94	0.94	0.93	-0.88	-0.88	-0.87	-0.06	-0.05	-0.05
2007	0.95	0.95	0.89	-0.93	-0.90	-0.86	-0.02	-0.02	-0.04
2008	0.91	0.91	0.92	-0.93	-0.94	-0.94	0.01	0.01	0.02
2009	0.95	0.96	0.97	-0.88	-0.89	-0.91	-0.07	-0.08	-0.06
2010	0.97	0.97	0.91	-0.93	-0.95	-0.88	-0.04	-0.04	-0.03
2011	0.92	0.93	0.95	-0.86	-0.88	-0.92	-0.06	-0.07	-0.04
2012	0.89	0.95	0.96	-0.76	-0.83	-0.88	-0.13	-0.19	-0.08

4.10.6 Appendix F

In Table 4.10-6 below we present the returns and volatility measured across by our long-short portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-6 Displays the returns and volatility measured across the different time horizons on the long-short portfolio against the market

	L/S Vol 12	L/S Vol 7	L/S Vol 3	POR L/S 12	POR L/S 7	POR L/S 3	Mark Vol 12	Mark Vol 7	Mark Vol 3	Mark Ret 12	Mark Ret 7	Mark Ret 3
1991	14.77%	15.76%	16.98%	29.07%	14.38%	-2.29%	6.33%	6.73%	7.40%	11.48%	6.05%	-0.15%
1992	13.63%	13.62%	13.95%	34.13%	41.97%	26.63%	5.10%	5.05%	5.58%	7.33%	9.92%	11.60%
1993	14.54%	15.26%	17.22%	24.46%	14.51%	7.76%	6.08%	6.44%	7.27%	10.76%	4.99%	1.84%
1994	12.47%	11.51%	10.83%	56.46%	52.86%	72.58%	6.28%	5.38%	5.48%	27.32%	28.16%	31.56%
1995	13.72%	14.29%	13.24%	39.02%	27.03%	36.66%	7.04%	7.01%	6.25%	20.57%	16.10%	18.01%
1996	18.94%	19.30%	15.26%	61.10%	57.18%	75.71%	10.73%	11.12%	9.35%	33.56%	26.59%	41.74%
1997	27.24%	30.38%	18.56%	-8.94%	-37.56%	-4.01%	13.69%	14.69%	9.05%	12.91%	1.09%	7.30%
1998	18.86%	16.24%	15.68%	44.84%	39.92%	86.45%	12.19%	11.19%	11.29%	24.63%	19.92%	30.98%
1999	27.75%	25.31%	27.99%	38.68%	23.97%	40.04%	16.37%	15.62%	18.71%	-15.68%	-9.91%	0.17%
2000	28.30%	31.15%	32.64%	36.48%	24.08%	62.82%	13.14%	14.42%	15.35%	-6.71%	-12.92%	2.70%
2001	35.25%	39.12%	29.05%	-30.56%	-48.61%	-25.34%	16.79%	18.65%	13.84%	-15.64%	-23.69%	-28.00%
2002	26.07%	27.78%	30.95%	93.53%	114.41%	141.21%	9.59%	10.50%	11.91%	29.52%	35.60%	44.04%
2003	20.17%	21.47%	21.93%	25.94%	19.54%	28.26%	7.14%	7.53%	7.85%	8.97%	7.59%	9.66%
2004	18.19%	19.15%	19.93%	32.73%	20.63%	52.79%	6.76%	7.18%	7.33%	15.34%	10.24%	18.62%
2005	19.61%	20.99%	23.06%	30.73%	22.00%	19.31%	7.92%	8.18%	9.39%	15.23%	12.14%	3.46%
2006	30.74%	24.01%	17.64%	-17.69%	-14.63%	15.46%	12.34%	9.99%	7.12%	3.22%	13.03%	16.92%
2007	74.25%	60.37%	29.45%	-54.81%	-134.83%	-38.37%	29.83%	25.71%	11.36%	-38.11%	-68.48%	-17.41%
2008	34.97%	41.03%	50.39%	109.49%	127.56%	122.32%	13.66%	15.68%	19.37%	37.34%	41.20%	32.38%
2009	30.85%	35.38%	40.55%	35.01%	24.24%	-15.54%	11.98%	13.75%	16.27%	14.97%	10.78%	-14.37%
2010	40.13%	44.44%	21.94%	2.03%	-6.33%	2.83%	15.35%	17.17%	9.10%	5.01%	2.16%	2.37%
2011	22.08%	23.53%	27.45%	44.66%	16.41%	0.66%	8.92%	9.62%	10.93%	16.65%	9.31%	1.72%
2012	19.26%	19.92%	22.69%	56.02%	50.96%	31.53%	7.43%	8.01%	9.15%	23.14%	21.03%	11.72%

4.10.7 Appendix G

In Table 4.10-7 below we present the returns across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-7 Displays returns for the different time horizons on our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	29.07%	22.39%	24.19%	14.38%	6.61%	7.99%	-2.29%	-14.27%	-17.52%
1992	34.13%	31.79%	39.90%	41.97%	36.88%	59.16%	26.63%	18.99%	31.84%
1993	24.46%	22.92%	15.22%	14.51%	11.47%	-3.61%	7.76%	2.31%	-9.25%
1994	56.46%	53.31%	55.06%	52.86%	48.38%	48.06%	75.35%	69.15%	69.17%
1995	39.02%	34.05%	31.42%	27.03%	25.19%	21.37%	36.66%	43.51%	33.49%
1996	61.10%	58.64%	58.82%	57.18%	56.77%	57.06%	75.71%	73.86%	56.50%
1997	-8.94%	-10.09%	-5.48%	-37.56%	-37.52%	-33.79%	-4.01%	-11.13%	-2.84%
1998	44.84%	44.28%	45.87%	39.92%	33.56%	32.71%	86.45%	78.24%	87.85%
1999	38.68%	35.89%	37.55%	23.97%	23.35%	32.74%	40.04%	32.08%	40.85%
2000	36.48%	33.34%	36.94%	24.08%	29.04%	18.53%	62.82%	63.53%	67.95%
2001	-30.56%	-33.54%	-29.53%	-48.61%	-56.70%	-50.47%	-25.34%	-44.86%	-72.17%
2002	93.53%	97.05%	114.11%	114.41%	121.06%	124.05%	141.21%	142.63%	187.42%
2003	25.94%	24.16%	28.48%	19.54%	15.11%	16.91%	28.26%	18.73%	11.31%
2004	32.73%	30.96%	35.33%	20.63%	19.68%	23.45%	52.79%	54.58%	60.03%
2005	30.73%	35.16%	31.46%	22.00%	23.16%	21.90%	19.31%	14.90%	15.05%
2006	-17.69%	-14.69%	-8.72%	-14.63%	-18.29%	-11.46%	15.46%	17.86%	30.47%
2007	-54.81%	-58.75%	-70.07%	-134.83%	-142.38%	-142.97%	-38.37%	-18.70%	-17.16%
2008	109.49%	110.78%	118.97%	127.56%	132.78%	146.80%	122.32%	133.71%	130.42%
2009	35.01%	38.00%	42.98%	24.24%	26.85%	30.61%	-15.54%	-15.43%	-16.91%
2010	2.03%	3.90%	-6.67%	-6.33%	-5.25%	-19.02%	2.83%	10.03%	-26.60%
2011	44.66%	43.89%	30.68%	16.41%	17.27%	0.44%	0.66%	-6.65%	-27.29%
2012	56.02%	62.04%	54.00%	50.96%	52.77%	42.91%	31.53%	33.76%	15.74%

4.10.8 Appendix H

In Table 4.10-8 below we present the returns across our long portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-8 Displays returns for the different time horizons for our three long portfolios

	L 12 Port1	L 12 Port2	L 12 Port3	L 7 Port1	L 7 Port2	L 7 Port3	L 3 Port1	L 3 Port2	L 3 Port3
1991	14.98%	10.44%	13.76%	9.02%	2.01%	0.58%	5.34%	-3.95%	-11.78%
1992	10.86%	9.34%	12.20%	15.44%	12.67%	17.10%	14.19%	4.43%	14.22%
1993	14.95%	14.17%	11.53%	8.36%	6.35%	6.18%	4.19%	0.89%	-7.39%
1994	29.43%	28.61%	32.51%	29.08%	28.71%	32.47%	37.01%	35.88%	32.77%
1995	17.89%	17.95%	12.80%	13.77%	14.37%	9.24%	20.54%	24.88%	20.32%
1996	29.73%	30.27%	32.51%	24.58%	27.20%	28.23%	39.01%	38.40%	35.78%
1997	-4.66%	-5.98%	-6.36%	-15.33%	-14.55%	-12.13%	-1.25%	-2.75%	-2.76%
1998	13.66%	11.86%	12.28%	12.14%	9.58%	6.09%	33.04%	29.93%	15.25%
1999	17.15%	21.54%	17.06%	11.53%	16.70%	22.06%	23.51%	25.19%	25.64%
2000	14.08%	16.26%	17.57%	8.21%	11.96%	14.80%	24.92%	25.17%	20.84%
2001	-16.97%	-14.88%	-14.35%	-22.72%	-20.32%	-19.36%	-16.01%	-22.87%	-21.68%
2002	38.84%	39.11%	40.07%	46.62%	46.51%	43.57%	55.10%	57.06%	47.94%
2003	12.20%	9.36%	13.06%	10.06%	7.10%	13.16%	13.18%	5.23%	10.37%
2004	19.18%	20.57%	20.56%	12.29%	16.17%	20.69%	26.60%	34.31%	30.86%
2005	16.80%	21.45%	17.40%	12.01%	15.64%	10.97%	8.45%	9.44%	2.83%
2006	0.08%	0.15%	2.96%	2.71%	-1.02%	3.01%	9.47%	11.41%	13.20%
2007	-27.40%	-28.50%	-37.53%	-58.97%	-60.85%	-65.86%	-8.18%	-10.51%	-14.35%
2008	46.34%	46.17%	33.42%	51.84%	53.90%	39.62%	41.81%	47.84%	36.26%
2009	21.32%	20.95%	20.68%	15.30%	15.77%	9.76%	-11.46%	-11.02%	-25.10%
2010	5.14%	5.51%	7.73%	-0.91%	-0.21%	-1.10%	3.35%	5.08%	4.68%
2011	14.94%	14.14%	10.37%	2.79%	2.92%	-0.80%	-4.82%	-10.09%	-18.58%
2012	28.25%	29.81%	30.42%	25.83%	28.66%	28.12%	12.32%	14.91%	9.80%

4.10.9 Appendix I

In Table 4.10-9 below we present the returns across our short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-9 Displays returns for the different time horizons for our three short portfolios

	S 12 Port1	S 12 Port2	S 12 Port3	S 7 Port1	S 7 Port2	S 7 Port3	S 3 Port1	S 3 Port2	S 3 Port3
1991	-14.09%	-11.95%	-10.43%	-5.36%	-4.60%	-7.40%	7.63%	10.32%	5.75%
1992	-23.27%	-22.45%	-27.69%	-26.52%	-24.21%	-42.06%	-12.44%	-14.57%	-17.62%
1993	-9.51%	-8.75%	-3.68%	-6.15%	-5.13%	9.79%	-3.57%	-1.41%	1.86%
1994	-27.03%	-24.69%	-22.54%	-23.79%	-19.67%	-15.59%	-38.34%	-33.27%	-36.40%
1995	-21.14%	-16.10%	-18.62%	-13.26%	-10.82%	-12.14%	-16.12%	-18.63%	-13.17%
1996	-31.38%	-28.37%	-26.31%	-32.60%	-29.58%	-28.83%	-36.70%	-35.47%	-20.72%
1997	4.29%	4.12%	-0.88%	22.23%	22.97%	21.66%	2.76%	8.38%	0.08%
1998	-31.19%	-32.41%	-33.59%	-27.77%	-23.98%	-26.62%	-53.41%	-48.31%	-72.60%
1999	-21.53%	-14.36%	-20.49%	-12.44%	-6.65%	-10.69%	-16.53%	-6.89%	-15.21%
2000	-22.40%	-17.08%	-19.37%	-15.87%	-17.08%	-3.74%	-37.90%	-38.35%	-47.11%
2001	13.59%	18.66%	15.18%	25.89%	36.38%	31.12%	9.34%	21.99%	50.50%
2002	-54.69%	-57.94%	-74.05%	-67.80%	-74.55%	-80.48%	-86.11%	-85.57%	-139.48%
2003	-13.74%	-14.80%	-15.42%	-9.48%	-8.01%	-3.75%	-15.08%	-13.49%	-0.94%
2004	-13.55%	-10.39%	-14.78%	-8.33%	-3.51%	-2.76%	-26.19%	-20.27%	-29.18%
2005	-13.93%	-13.71%	-14.06%	-9.98%	-7.52%	-10.93%	-10.87%	-5.46%	-12.22%
2006	17.77%	14.85%	11.69%	17.34%	17.27%	14.48%	-5.99%	-6.45%	-17.27%
2007	27.41%	30.25%	32.54%	75.86%	81.53%	77.11%	30.19%	8.18%	2.81%
2008	-63.15%	-64.61%	-85.55%	-75.72%	-78.88%	-107.18%	-80.51%	-85.88%	-94.16%
2009	-13.68%	-17.05%	-22.29%	-8.94%	-11.08%	-20.85%	4.08%	4.41%	-8.20%
2010	3.11%	1.61%	14.39%	5.42%	5.04%	17.92%	0.51%	-4.95%	31.28%
2011	-29.72%	-29.75%	-20.30%	-13.63%	-14.35%	-1.23%	-5.48%	-3.45%	8.72%
2012	-27.77%	-32.23%	-23.59%	-25.12%	-24.11%	-14.79%	-19.21%	-18.85%	-5.94%

4.10.10 Appendix J

In Table 4.10-10 below we present the maximum drawdown across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-10 Displays the maximum drawdown expressed in percentage for our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	-9.13%	-12.20%	-13.66%	-9.13%	-12.20%	-13.66%	-9.13%	-12.20%	-13.66%
1992	-6.12%	-5.62%	-16.94%	-5.08%	-5.62%	-6.55%	-3.87%	-5.62%	-6.55%
1993	-12.98%	-11.12%	-15.16%	-10.79%	-9.76%	-11.58%	-7.97%	-8.29%	-9.92%
1994	-6.13%	-6.77%	-9.07%	-6.13%	-6.77%	-9.07%	-2.32%	-2.00%	-3.84%
1995	-12.89%	-14.17%	-13.23%	-12.89%	-14.17%	-13.23%	-6.57%	-7.15%	-5.75%
1996	-13.96%	-14.87%	-14.71%	-13.96%	-14.87%	-14.71%	-3.16%	-3.30%	-6.09%
1997	-62.12%	-59.37%	-48.99%	-62.12%	-59.37%	-48.99%	-13.22%	-15.01%	-13.01%
1998	-11.12%	-13.13%	-13.94%	-11.12%	-13.13%	-13.94%	-5.65%	-5.84%	-9.24%
1999	-15.83%	-16.54%	-17.67%	-14.74%	-15.84%	-15.93%	-12.56%	-13.60%	-14.72%
2000	-41.46%	-41.32%	-52.99%	-41.46%	-41.32%	-52.99%	-14.34%	-14.81%	-14.54%
2001	-67.94%	-75.51%	-70.81%	-67.94%	-75.51%	-70.81%	-21.78%	-28.80%	-37.40%
2002	-10.16%	-11.46%	-17.10%	-10.00%	-9.63%	-17.10%	-6.66%	-6.45%	-8.00%
2003	-11.87%	-13.91%	-14.02%	-11.87%	-13.91%	-14.02%	-10.96%	-12.76%	-12.41%
2004	-12.25%	-11.94%	-12.21%	-12.25%	-11.94%	-12.21%	-8.91%	-9.07%	-10.35%
2005	-12.75%	-14.80%	-16.72%	-12.75%	-14.80%	-16.72%	-12.75%	-14.80%	-16.72%
2006	-54.49%	-48.79%	-44.20%	-30.05%	-30.50%	-30.64%	-10.42%	-9.40%	-8.20%
2007	-143.94%	-145.00%	-156.41%	-128.60%	-133.48%	-131.90%	-22.44%	-15.16%	-12.76%
2008	-13.60%	-14.10%	-16.97%	-13.60%	-12.65%	-13.90%	-12.29%	-12.56%	-13.90%
2009	-22.10%	-20.35%	-22.36%	-22.10%	-20.35%	-22.36%	-22.10%	-20.35%	-22.36%
2010	-41.26%	-40.55%	-49.05%	-41.26%	-40.55%	-49.05%	-12.72%	-12.05%	-18.77%
2011	-10.46%	-12.27%	-17.58%	-10.46%	-12.27%	-17.58%	-10.46%	-12.27%	-17.58%
2012	-6.87%	-8.09%	-11.92%	-6.87%	-8.09%	-9.58%	-6.87%	-8.09%	-9.58%

4.10.11 Appendix K

In Table 4.10-11 below we present the Sharpe ratio across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-11 Displays the Sharpe ratio for our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	1.965	1.467	1.448	0.910	0.398	0.462	-0.138	-0.833	-0.928
1992	2.501	2.454	2.088	3.077	2.798	3.071	1.905	1.433	1.713
1993	1.679	1.612	0.967	0.947	0.764	-0.221	0.448	0.134	-0.492
1994	4.522	4.302	3.862	4.588	4.195	3.534	6.696	6.581	5.295
1995	2.841	2.468	2.190	1.888	1.745	1.445	2.764	3.241	2.335
1996	3.223	3.187	2.857	2.960	2.991	2.697	4.958	5.091	3.248
1997	-0.330	-0.382	-0.213	-1.238	-1.277	-1.199	-0.219	-0.560	-0.133
1998	2.375	2.393	2.167	2.456	2.032	1.674	5.511	4.872	4.309
1999	1.392	1.263	1.278	0.945	0.902	1.161	1.428	1.113	1.332
2000	1.288	1.121	1.148	0.771	0.890	0.520	1.923	1.810	1.807
2001	-0.868	-0.901	-0.760	-1.244	-1.370	-1.180	-0.874	-1.409	-1.901
2002	3.586	3.678	3.620	4.117	4.375	3.608	4.561	4.676	4.734
2003	1.284	1.185	1.361	0.908	0.692	0.758	1.286	0.844	0.501
2004	1.797	1.737	1.858	1.074	1.043	1.161	2.646	2.786	2.871
2005	1.564	1.761	1.575	1.045	1.065	1.018	0.835	0.617	0.638
2006	-0.577	-0.530	-0.299	-0.611	-0.830	-0.495	0.874	1.049	1.652
2007	-0.739	-0.875	-1.039	-2.234	-2.585	-2.617	-1.304	-0.684	-0.615
2008	3.130	3.329	3.338	3.108	3.470	3.648	2.427	2.853	2.652
2009	1.133	1.244	1.283	0.684	0.768	0.799	-0.384	-0.388	-0.405
2010	0.049	0.099	-0.166	-0.144	-0.120	-0.428	0.127	0.451	-1.098
2011	2.021	2.003	1.411	0.696	0.729	0.019	0.022	-0.245	-1.042
2012	2.906	3.108	2.334	2.556	2.562	1.887	1.388	1.429	0.609

4.10.12 Appendix L

In Table 4.10-12 below we present the Treynor ratio across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-12 Displays the Treynor ratio for our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	0.114	0.080	0.221	0.044	0.005	0.073	-0.035	-0.098	-0.162
1992	0.137	0.149	0.508	0.180	0.183	0.830	0.104	0.086	0.371
1993	0.092	0.101	0.120	0.044	0.042	-0.062	0.013	-0.003	-0.116
1994	0.305	0.297	0.517	0.265	0.249	0.441	0.412	0.416	0.685
1995	0.201	0.170	0.272	0.121	0.105	0.160	0.169	0.198	0.279
1996	0.350	0.285	0.520	0.329	0.275	0.490	0.494	0.399	0.534
1997	-0.080	-0.090	-0.107	-0.224	-0.232	-0.376	-0.050	-0.086	-0.083
1998	0.360	0.367	0.398	0.356	0.307	0.281	1.154	1.177	0.890
1999	0.237	0.213	0.349	0.145	0.139	0.317	0.281	0.209	0.369
2000	0.159	0.133	0.269	0.096	0.111	0.108	0.295	0.274	0.523
2001	-0.180	-0.182	-0.282	-0.272	-0.294	-0.459	-0.161	-0.236	-0.638
2002	0.361	0.373	0.998	0.460	0.487	1.092	0.579	0.592	1.730
2003	0.080	0.086	0.234	0.055	0.051	0.133	0.089	0.065	0.084
2004	0.112	0.119	0.285	0.063	0.073	0.182	0.188	0.207	0.482
2005	0.110	0.135	0.238	0.070	0.080	0.157	0.061	0.048	0.101
2006	-0.097	-0.089	-0.113	-0.086	-0.108	-0.137	0.045	0.057	0.215
2007	-0.250	-0.282	-0.602	-0.622	-0.690	-1.196	-0.180	-0.101	-0.186
2008	0.430	0.469	0.954	0.490	0.560	1.185	0.471	0.570	1.040
2009	0.123	0.156	0.363	0.079	0.109	0.258	-0.085	-0.065	-0.140
2010	-0.012	0.015	-0.054	-0.045	-0.021	-0.151	-0.009	0.042	-0.218
2011	0.172	0.187	0.262	0.049	0.072	0.003	-0.018	-0.027	-0.222
2012	0.219	0.187	0.262	0.197	0.072	0.003	0.112	-0.027	-0.222

4.10.13 Appendix M

In Table 4.10-13 below we present the Information ratio across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-13 Displays the Information ratio for our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	1.963	1.467	1.444	0.909	0.399	0.460	-0.133	-0.821	-0.917
1992	2.497	2.450	2.084	3.066	2.787	3.059	1.888	1.420	1.696
1993	1.678	1.610	0.966	0.946	0.763	-0.219	0.446	0.134	-0.485
1994	4.514	4.293	3.854	4.570	4.179	3.520	6.627	6.512	5.240
1995	2.837	2.466	2.188	1.882	1.740	1.442	2.737	3.209	2.313
1996	3.216	3.181	2.851	2.949	2.980	2.686	4.907	5.038	3.215
1997	-0.327	-0.379	-0.210	-1.231	-1.269	-1.191	-0.214	-0.551	-0.129
1998	2.371	2.389	2.164	2.447	2.026	1.669	5.454	4.821	4.264
1999	1.390	1.261	1.276	0.943	0.900	1.157	1.414	1.102	1.319
2000	1.286	1.119	1.147	0.769	0.888	0.520	1.904	1.792	1.788
2001	-0.864	-0.898	-0.757	-1.237	-1.363	-1.174	-0.863	-1.392	-1.879
2002	3.578	3.668	3.610	4.099	4.355	3.592	4.512	4.625	4.682
2003	1.283	1.183	1.358	0.906	0.689	0.755	1.275	0.835	0.496
2004	1.795	1.733	1.854	1.072	1.038	1.156	2.619	2.756	2.840
2005	1.563	1.758	1.572	1.043	1.062	1.014	0.828	0.611	0.632
2006	-0.574	-0.527	-0.296	-0.604	-0.824	-0.491	0.867	1.041	1.636
2007	-0.736	-0.872	-1.035	-2.223	-2.572	-2.604	-1.288	-0.675	-0.607
2008	3.123	3.320	3.330	3.094	3.454	3.632	2.401	2.822	2.623
2009	1.132	1.240	1.280	0.682	0.764	0.796	-0.379	-0.384	-0.401
2010	0.050	0.099	-0.165	-0.142	-0.120	-0.425	0.128	0.446	-1.086
2011	2.017	1.997	1.407	0.694	0.726	0.019	0.024	-0.243	-1.030
2012	2.901	3.099	2.327	2.534	2.550	1.878	1.374	1.413	0.602

4.10.14 Appendix N

In Table 4.10-14 below we present the Information ratio across our long-short portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 4.10-14 Displays the Sortino ratio for our three long-short portfolios

	L/S 12 Port1	L/S 12 Port2	L/S 12 Port3	L/S 7 Port1	L/S 7 Port2	L/S 7 Port3	L/S 3 Port1	L/S 3 Port2	L/S 3 Port3
1991	2.892	2.119	2.238	1.403	0.595	0.751	-0.208	-1.308	-1.513
1992	3.705	3.649	3.072	4.734	4.288	4.721	2.736	2.118	2.564
1993	2.491	2.475	1.500	1.364	1.144	-0.330	0.641	0.203	-0.763
1994	5.612	5.560	5.581	6.382	5.932	5.593	10.687	11.349	9.320
1995	3.878	3.426	3.223	2.401	2.248	2.060	3.510	4.572	3.354
1996	3.473	3.495	3.168	2.810	2.893	2.700	6.803	7.364	5.194
1997	-0.462	-0.547	-0.300	-1.669	-1.753	-1.670	-0.332	-0.911	-0.232
1998	4.271	4.040	3.641	4.524	3.532	2.913	9.990	8.980	6.748
1999	2.381	2.143	2.243	1.518	1.462	1.986	2.139	1.687	2.242
2000	2.168	1.852	1.855	1.278	1.427	0.829	3.394	3.048	2.989
2001	-1.479	-1.534	-1.387	-2.118	-2.311	-2.175	-1.707	-2.784	-3.835
2002	5.642	5.781	5.952	6.148	6.445	5.643	6.649	6.756	7.212
2003	1.915	1.763	2.037	1.307	1.004	1.102	1.697	1.171	0.715
2004	2.979	2.893	3.114	1.767	1.739	1.995	4.386	4.842	4.866
2005	2.238	2.506	2.341	1.761	1.802	1.799	1.366	1.040	1.137
2006	-0.824	-0.760	-0.423	-0.805	-1.101	-0.652	1.251	1.468	2.519
2007	-1.046	-1.211	-1.433	-3.041	-3.387	-3.374	-2.098	-1.076	-0.913
2008	4.502	4.792	4.942	4.758	5.291	5.564	3.702	4.375	4.157
2009	1.687	1.863	1.997	1.058	1.199	1.309	-0.575	-0.581	-0.632
2010	0.066	0.132	-0.224	-0.178	-0.151	-0.553	0.193	0.754	-1.579
2011	3.202	3.132	2.324	1.126	1.178	0.033	0.036	-0.360	-1.801
2012	4.166	4.048	3.332	3.500	3.361	2.507	1.813	1.728	0.726

4.10.15 Appendix O

In Table 4.10-15 below we present the number of stocks across our long and short portfolios.

Table 4.10-15 Displays number of stocks per year when screening by portfolio type

	S Port 1	L Port 1	S Port 2	L Port 2	S Port 3	L Port 3	L Port 4
1991	603	92	535	66	158	30	6
1992	242	191	219	117	33	78	5
1993	223	192	223	117	60	50	8
1994	732	185	625	132	178	99	3
1995	551	245	484	150	114	88	10
1996	389	278	376	176	108	100	10
1997	422	294	387	176	68	127	12
1998	454	277	425	190	150	91	11
1999	380	288	341	174	112	80	11
2000	548	196	469	130	176	62	11
2001	482	201	448	128	122	76	8
2002	414	338	365	242	97	102	6
2003	329	311	290	221	83	120	12
2004	383	285	356	180	151	83	6
2005	526	245	404	146	101	80	8
2006	397	328	322	217	96	110	3
2007	403	252	304	189	145	52	3
2008	459	182	368	129	150	36	3
2009	236	369	206	289	47	166	10
2010	287	327	245	218	60	149	4
2011	365	233	316	136	67	81	3
2012	280	299	242	216	48	147	5

4.10.16 Appendix P

In Table 4.10-16 we present the returns earned by our long "Portfolio 1" and "Portfolio 4".

Table 4.10-16 Displays returns for our long "Portfolio 1" and long "Portfolio 4" on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	14.98%	-5.82%	9.02%	-6.17%	5.34%	-54.55%
1992	10.86%	-19.06%	15.44%	-25.03%	14.19%	-75.46%
1993	14.95%	-21.38%	8.36%	-23.55%	4.19%	-26.99%
1994	29.43%	3.15%	29.08%	33.99%	37.01%	98.18%
1995	17.89%	2.18%	13.77%	9.84%	20.54%	6.11%
1996	29.73%	41.03%	24.58%	30.94%	39.01%	33.99%
1997	-4.66%	7.12%	-15.33%	-8.88%	-1.25%	24.82%
1998	13.66%	17.41%	12.14%	4.16%	33.04%	1.48%
1999	17.15%	6.44%	11.53%	27.15%	23.51%	50.04%
2000	14.08%	17.97%	8.21%	52.18%	24.92%	29.00%
2001	-16.97%	-12.04%	-22.72%	-13.31%	-16.01%	-53.70%
2002	38.84%	46.07%	46.62%	75.23%	55.10%	97.98%
2003	12.20%	-23.18%	10.06%	-8.94%	13.18%	-6.32%
2004	19.18%	22.92%	12.29%	16.13%	26.60%	22.41%
2005	16.80%	24.93%	12.01%	25.50%	8.45%	37.90%
2006	0.08%	8.35%	2.71%	9.79%	9.47%	33.71%
2007	-27.40%	-31.92%	-58.97%	-54.58%	-8.18%	-11.92%
2008	46.34%	76.44%	51.84%	102.76%	41.81%	80.64%
2009	21.32%	3.03%	15.30%	7.67%	-11.46%	-4.11%
2010	5.14%	6.98%	-0.91%	9.32%	3.35%	5.74%
2011	14.94%	37.79%	2.79%	16.82%	-4.82%	-27.13%
2012	28.25%	23.92%	25.83%	35.64%	12.32%	39.79%

4.10.17 Appendix Q

In Table 4.10-17 we present the maximum drawdown earned by our long "Portfolio 1" and "Portfolio 4".

Table 4.10-17 Displays the maximum drawdown for our long "Portfolio 1" and long "Portfolio 4" on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	-5.38%	-34.00%	-5.38%	-34.00%	-5.38%	-29.17%
1992	-3.65%	-51.90%	-2.43%	-40.50%	-2.43%	-40.52%
1993	-5.53%	-50.60%	-5.53%	-28.10%	-4.71%	-22.00%
1994	-2.15%	-83.90%	-1.74%	-52.40%	-1.02%	-14.69%
1995	-6.62%	-13.60%	-6.62%	-11.80%	-2.43%	-7.30%
1996	-7.47%	-12.80%	-7.47%	-11.70%	-1.43%	-6.09%
1997	-25.60%	-54.20%	-25.60%	-54.20%	-6.22%	-33.80%
1998	-7.80%	-25.10%	-7.80%	-12.30%	-3.05%	-9.41%
1999	-8.34%	-28.40%	-5.85%	-19.50%	-5.49%	-10.08%
2000	-25.78%	-31.30%	-25.78%	-31.30%	-11.01%	-31.30%
2001	-30.27%	-36.00%	-30.27%	-36.00%	-9.99%	-32.24%
2002	-4.40%	-17.40%	-3.48%	-15.90%	-1.86%	-15.93%
2003	-5.88%	-62.80%	-5.22%	-27.90%	-5.03%	-12.87%
2004	-4.57%	-10.10%	-4.57%	-10.10%	-4.47%	-10.10%
2005	-8.63%	-11.00%	-8.63%	-9.10%	-8.63%	-9.08%
2006	-14.51%	-33.00%	-12.30%	-25.50%	-5.69%	-6.58%
2007	-65.34%	-79.00%	-56.69%	-67.20%	-7.89%	-11.29%
2008	-5.76%	-18.60%	-5.76%	-12.90%	-5.76%	-12.93%
2009	-10.80%	-15.60%	-10.80%	-11.50%	-10.80%	-10.65%
2010	-19.40%	-16.50%	-19.40%	-16.50%	-5.39%	-6.07%
2011	-6.73%	-37.20%	-6.73%	-37.20%	-6.73%	-34.46%
2012	-4.11%	-9.80%	-4.04%	-8.20%	-4.04%	-6.60%

4.10.18 Appendix R

In Table 4.10-18 we present the Sharpe ratio earned by our long “Portfolio 1” and “Portfolio 4”.

Table 4.10-18 Displays the Sharpe ratio for our long “Portfolio 1” and long “Portfolio 4” on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	1.685	-0.211	0.948	-0.213	0.534	-1.850
1992	1.726	-0.711	2.499	-0.883	2.044	-1.963
1993	1.948	-0.851	1.038	-0.913	0.465	-0.948
1994	4.439	0.058	4.803	0.680	6.007	2.440
1995	2.410	0.120	1.758	0.486	3.078	0.336
1996	3.156	1.832	2.542	1.459	4.987	1.831
1997	-0.375	0.200	-1.121	-0.217	-0.137	0.644
1998	1.372	0.748	1.397	0.206	3.850	0.085
1999	1.274	0.204	0.986	0.919	1.832	1.898
2000	0.900	0.433	0.475	1.165	1.334	0.589
2001	-0.975	-0.433	-1.168	-0.422	-1.102	-1.862
2002	3.844	1.437	4.366	1.950	4.712	2.188
2003	1.266	-0.849	0.989	-0.445	1.258	-0.313
2004	2.181	1.246	1.305	0.801	2.722	0.945
2005	1.665	1.327	1.082	1.226	0.680	1.894
2006	0.002	0.282	0.216	0.382	1.041	2.042
2007	-0.827	-0.518	-2.226	-0.955	-0.608	-0.622
2008	3.197	2.269	3.095	2.629	2.094	1.756
2009	1.485	0.162	0.914	0.389	-0.583	-0.173
2010	0.244	0.354	-0.041	0.433	0.301	0.455
2011	1.367	1.195	0.239	0.450	-0.376	-0.855
2012	2.870	1.404	2.529	2.507	1.039	2.944

4.10.19 Appendix S

In Table 4.10-19 we present the Treynor ratio earned by our long “Portfolio 1” and “Portfolio 4”.

Table 4.10-19 Displays the Treynor ratio for our long “Portfolio 1” and long “Portfolio 4” on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	0.089	-0.171	0.036	-0.169	0.003	-0.756
1992	0.061	-0.726	0.116	-0.762	0.100	-1.831
1993	0.095	-0.532	0.033	-0.539	-0.008	-0.827
1994	0.296	-0.013	0.274	0.523	0.367	1.777
1995	0.148	-0.075	0.094	0.098	0.169	0.015
1996	0.325	0.811	0.251	0.513	0.470	0.718
1997	-0.120	0.042	-0.238	-0.305	-0.069	0.438
1998	0.175	0.375	0.159	-0.018	0.952	-0.083
1999	0.187	0.036	0.114	0.756	0.331	1.758
2000	0.085	0.137	0.029	0.512	0.177	0.245
2001	-0.228	-0.203	-0.287	-0.202	-0.231	-0.676
2002	0.351	0.817	0.445	1.471	0.550	1.677
2003	0.058	-0.404	0.041	-0.162	0.067	-0.100
2004	0.119	0.243	0.060	0.161	0.175	0.214
2005	0.102	0.289	0.057	0.289	0.028	0.432
2006	-0.044	0.044	-0.020	0.067	0.038	0.359
2007	-0.306	-0.435	-0.656	-0.812	-0.124	-0.248
2008	0.428	0.826	0.480	1.112	0.390	0.901
2009	0.144	0.035	0.089	0.091	-0.140	-0.045
2010	0.001	0.077	-0.045	0.103	-0.015	0.076
2011	0.088	0.439	-0.020	0.186	-0.087	-0.270
2012	0.197	0.439	0.173	0.186	0.059	-0.270

4.10.20 Appendix T

In Table 4.10-20 we present the Information ratio earned by our long “Portfolio 1” and “Portfolio 4”.

Table 4.10-20 Displays the Information ratio for our long “Portfolio 1” and long “Portfolio 4” on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	1.686	-0.209	0.949	-0.210	0.534	-1.828
1992	1.729	-0.708	2.495	-0.877	2.029	-1.940
1993	1.949	-0.848	1.039	-0.907	0.466	-0.936
1994	4.434	0.058	4.788	0.678	5.949	2.414
1995	2.410	0.122	1.756	0.486	3.052	0.335
1996	3.153	1.830	2.535	1.454	4.939	1.814
1997	-0.370	0.200	-1.112	-0.215	-0.131	0.639
1998	1.373	0.748	1.396	0.207	3.813	0.087
1999	1.274	0.205	0.986	0.916	1.816	1.879
2000	0.901	0.433	0.476	1.161	1.322	0.584
2001	-0.970	-0.431	-1.160	-0.419	-1.087	-1.841
2002	3.838	1.434	4.350	1.941	4.664	2.164
2003	1.267	-0.846	0.989	-0.442	1.249	-0.309
2004	2.181	1.242	1.304	0.798	2.697	0.935
2005	1.665	1.325	1.082	1.222	0.677	1.874
2006	0.006	0.283	0.218	0.382	1.035	2.023
2007	-0.823	-0.516	-2.214	-0.950	-0.598	-0.612
2008	3.192	2.263	3.084	2.617	2.073	1.737
2009	1.485	0.161	0.913	0.388	-0.574	-0.171
2010	0.246	0.353	-0.039	0.431	0.302	0.450
2011	1.368	1.192	0.242	0.447	-0.368	-0.846
2012	2.867	1.400	2.510	2.495	1.032	2.912

4.10.21 Appendix U

In Table 4.10-21 we present the Sortino ratio earned by our long “Portfolio 1” and “Portfolio 4”.

Table 4.10-21 Displays the Sortino ratio for our long “Portfolio 1” and long “Portfolio 4” on the different windows

	L 12 Port1	L 12 Port4	L 7 Port1	L 7 Port4	L 3 Port1	L 3 Port4
1991	2.484	-0.304	1.393	-0.281	0.903	-2.667
1992	2.621	-0.712	4.071	-0.773	3.364	-1.711
1993	3.040	-1.137	1.643	-1.160	0.751	-1.122
1994	6.850	0.080	8.906	0.866	13.638	3.302
1995	3.484	0.216	2.403	0.924	3.940	0.560
1996	3.673	2.898	2.693	2.011	7.265	2.998
1997	-0.533	0.239	-1.549	-0.256	-0.209	0.891
1998	2.578	1.295	2.538	0.278	7.300	0.130
1999	2.358	0.342	1.736	1.412	2.999	2.612
2000	1.517	0.769	0.795	2.051	2.412	0.964
2001	-1.654	-0.623	-1.983	-0.688	-2.203	-2.979
2002	6.494	2.234	6.922	3.165	7.600	3.929
2003	1.956	-0.977	1.490	-0.625	1.750	-0.526
2004	3.697	1.674	2.245	1.050	4.292	1.115
2005	2.434	2.007	1.787	1.840	1.085	3.232
2006	0.008	0.311	0.281	0.333	1.433	2.401
2007	-1.136	-0.651	-2.853	-1.188	-0.878	-0.883
2008	4.851	3.605	4.845	4.428	3.216	2.953
2009	2.119	0.223	1.349	0.509	-0.863	-0.249
2010	0.325	0.423	-0.050	0.495	0.431	0.576
2011	2.154	2.317	0.406	0.941	-0.606	-1.500
2012	3.942	1.651	3.375	4.599	1.351	5.728

Chapter five – Return on equity (ROE) momentum strategy

5.1 Introduction

Several studies such as Penman (1991) have documented that return on equity (ROE) is not particularly a useful measure for delivering alpha as it contains little information related to future stock returns. However, controversial points of view disperse here as ROE is presumably one of the favourite measures used by practitioners when assessing a stock in which to invest.

By definition, ROE is a summary of the profitability of the firm over a period of time. Similarly, someone could have used return on assets (ROA), which is also a measure of profitability for all contributors of capital. It is defined as earnings before interest taxes divided by total assets. However, in this study we focus only on ROE, which is defined as net income divided by shareholder's equity – see later formula.

As stated, ROE is a factor to determine a firm's growth rate of earnings. Practitioners as well as academicians have recently started to assume that future ROE will approximate its past value; solely a high ROE does not imply necessarily that the future ROE will be high. On the other hand, a declining ROE is an indication that the firm's new investment has delivered a lower ROE than past investment.

In this chapter, we show how an investor can use ROE as input into stock valuation analysis. By focusing on our ROE momentum strategy, we are able to show that the ROE can be a useful measure when forming a portfolio. This is new and has not been done in the past, the novelty of our work is in fact to use a financial measure to form a momentum strategy. Using three-year ROE as a trading strategy we are able to report subsequent return for investor's willing to benefit from our strategy.

Every fiscal year we screen the S&P 1500 index. Using a momentum methodology we give a binary signal (0 or 1) for each stock based on the ROE criteria if this one is greater during three following years. We then propose a "BUY" portfolio based on the stocks highlighted by our model in order to give investors a chance to assess the relevance of the criteria we have selected.

We believe that this strategy can help investors and portfolio managers to understand the dynamics of the stocks in their portfolio and to form better investment ideas, as it appears that the ROE enables them to pick stock with higher returns.

The rest of the chapter is outlined as follows, the first part of the chapter give some insight into the literature review around ROE, stock returns and momentum. The second part summarizes the methodology principles as well as the risk-adjusted performances used to describe our results. Finally, the third part presents the empirical results gained from implementing the strategy based on stocks selected by our model.

5.2 Literature Review

We review in this part the different studies on return on equity (ROE) momentum, including some insight into the premise of momentum strategies, ROE as a profitability measure, ROE and stock returns, some literature on portfolios formed on the basis of ROE and, finally, we try to focus on literature that has used ROE as a momentum strategy.

5.2.1 Momentum strategies

Several studies have documented the use of momentum strategies applied to different anomalies. Here we give a brief summary of some of them.

DeBont and Thaler (1985) were among the first to document a long-term over-reaction in stock returns; they argued that stocks that had performed poorly over the previous three to five years were more likely to outperform over the next three to five years.

Strategies based on earnings surprises are often referred to as momentum strategies as, more often than not, they lead to purchases of stocks which have outperformed the market over the previous six months. Chan et al. (1996) showed that stocks with positive earnings momentum have regularly outperformed the US market since 1977 and attributed the momentum effect around earnings announcement. For instance, they suggest that sorting stocks by prior six-month returns yields investors a return of 8.8% over the subsequent six months. Also, ranking stocks by a moving average based on revisions in consensus estimates produces a 7.7% return over the subsequent six months.

Previously, Levy (1967) claimed that investors who buy stocks with a current price that is subsequently higher than the average stock price realized over the past 27 weeks are able to benefit from abnormal returns. Also, the author argued that superior profits can be realized by investing in stocks which historically have been strong in price movement solely; investors should determine the riskiness of the strategy employed using various technical measures.

Jegadeesh and Titman (1993) studied the momentum effect focusing on the US market over the period 1965 to 1989. They considered a strategy that buys stocks based on their return over the past first, second, third and fourth quarters and suggested that stocks that generate higher than average returns in one period also generate higher than average returns in the following period. This shows that there is a form of momentum in stock prices. In fact, they argued that past winners consistently generate higher returns around their earnings announcements in the seven months following the portfolio formation, in contrast with past losers. They reported that investors can realize a compounded excess return of 12.01% per year on average using their strategy.

Similarly, Jegadeesh and Titman (2001) demonstrated that, while the performance of individual stocks is highly unpredictable, portfolios of best-performing stocks in the recent past period appear to outperform other stocks which were lagging in the past period, and argued that the momentum effect presumably represents the strongest evidence against the market efficiency hypothesis.

As part of his analysis on the role of momentum strategies to be applied in different countries, Rouwenhorst (1998) found that momentum strategies were profitable for equities in 12 European markets over the period 1980-1995. This result suggests that a diversified portfolio of past winners outperformed a portfolio of past losers by 1% on average per month. Griffin et al. (2003) examined momentum profits in different countries and found that momentum yields to subsequent return in most of those countries when investors are seeking to form a portfolio based on a momentum strategy. They also investigated the relation between momentum returns and macroeconomic risk and suggested that if macroeconomic risk is driving momentum then momentum should be country specific. Additionally, Meade and Beasley (2011) showed that momentum effects exist for a global range of stock markets and suggested that macroeconomic risks that are driving momentum return are country specific. They investigated the S&P 1200 using data from DataStream from January 1999 to September 2006 and offered a Sortino ratio-type portfolio which generates profits in excess of the market.

In a similar manner, Chan et al. (2000) examined the profitability of momentum strategies implemented in international stock market indices. The literature has suggested over the past few years that stock returns are predictable based on historical price. Firstly, they implemented the momentum strategy on individual stocks, then they examined whether the profitability of momentum strategy is affected by exchange rate movement and, finally, they examined whether trading volume affects the profitability of momentum strategies. Their results are both statistically and economically significant when using momentum strategies based on past returns.

Also, there is some research that stipulates that size, book to market or even beta might have an impact on momentum strategies. For instance, Hong et al. (2000) documented the importance of size or market capitalization on the magnitude of momentum returns and showed that small firms tend to have a decline in momentum profits. Likewise, Siganos (2013) looked at different characteristics of the firms to explore the momentum patterns such as book to market, size, beta, age, profit margin, current ratio, return on common equity, and return on capital. Using UK data from August 1988 to July 2006 extracted from DataStream, the results are suggestive of some form of pattern display in momentum strategies: that the momentum effect is driven by prior winners that keep performing well while prior losers keep performing poorly.

In summary, the momentum effect is driven mainly by prior winners which keep performing well instead of prior losers which tend to perform poorly.

5.2.2 Return on equity (ROE)/profitability

Several studies have made evident that ROE is a measure of profitability. The change in rate in ROE is helpful to understand whether the company will change its status.

Hergert (1983) investigated whether ROE is a reliable measure of corporate investment. The author said: "Return on equity plays a crucial role in formulating and implementing a firm's strategy" (p. 103, *Will Corporate Performance Decline in an Improving Economy?).*

In contrast, Lee and Li (2012) analyzed the effect of diversification on firm performance and used ROE as a measure of performance. Their results suggest that ROE is positively associated when a firm's performance is poor and negatively associated when a firm's performance is good. Also, they found that a firm's size has a positively significant effect on ROE, as well as debt ratio and a firm's ROE. As stated: "The link between the debt ratio and return on equity becomes significantly negative for quantiles between 0.05 and 0.25, consistent with the notion that a firm's positive leverage to earnings is weakened by the negative impact of debt ratio on earnings when the potential effect of bankruptcy cost on return on equity. Firms should pay more attention to their financial leverage when bankruptcy costs are present" (p. 2163, *Diversification and Risk-adjusted Performance: A Quantile Regression Approach*.)

However, Wet and Toit (2007) argued that ROE is a misleading measure of corporate financial performance; indeed, earnings can be manipulated and ROE will continue to rise with more financial leverage (as long as the returns earned on the borrowed funds exceed the cost of borrowing). Also, ROE may be subject to inflation (inflation has a negative impact on profit margin) and in the long term may reduce ROE. To emphasize our thoughts, companies with poor past returns and high ROE tend to manipulate their earnings; because this manipulation is only gradual the market fails to fully understand and stock return are in consequence not great. Also, past returns and high ROE are a sign that the company's true profitability has already peaked and will deteriorate in the future.

Therefore, there might be a controversial point of view suggesting that ROE of value stocks is more sensitive to the ROE of the market than is the ROE of growth stocks, and also stipulating that the ROE of growth stocks is more sensitive to the market's price earnings – see, for instance, Campbell et al. (2009).

Using data from CRSP and Compustat from January 1972 to December 2010, Chen and Lin (2011) measured ROE as net income before extraordinary items divided by one-quarter-lagged book equity. They found that there is asymmetrical mean reversion behaviour in ROE. The research investigates whether investor earnings optimism has an impact on the earnings management policy and in consequence on the ROE, and suggests that managers might manipulate reported earnings.

Additionally, Baker and Wurgler (2006), using monthly stock returns between 1963 and 2001, looked at patterns in stock returns and studied the effect of investor sentiment on stock returns and examined whether movement in ROE should be explained by change in investor's sentiment instead of the firm's operating environment.

On the other hand, Dhaliwal et al. (2010) investigated the relation between institutional ownership, financial health and the market valuation on earnings. Their results found that firms with a significant level of institutional ownership are healthier than firms with a low one and stipulated that high institutional ownership has higher ROE and ROA in the current year and subsequent three years whereas low institutional ownership displays low ROE and ROA in the current year and subsequent three years. In addition, Hessel and Norman (1992) found that firms with at least 65% of institutional ownership are more profitable in terms of ROE and ROA as they invest more in R&D.

In summary, several studies have focused on the aspect of ROE as a profitability measure. Profitability plays an essential role as it does not only measure the firm's ability to generate value from the invested capital but as well the firms are likely to adjust the operating performances.

5.2.3 Return on equity (ROE) and stock returns

A number of past studies have shown the link between accounting variables and stock price returns. Also, there is some significant evidence that ROE and stock returns might be linked as many investors look at ROE when targeting future return performances. Indeed, ROE is a useful indication of profitability, which in itself is a key determinant of stock prices.

Penman (1991) examined how ROE is good at pricing stock returns. Using data over the period 1969 to 1986, one of the main questions described in the paper is to what extent ROE captures stock returns. After multiple regressions, the results suggested a positive relation between stock return and ROE; also, firms with high (low) current ROE tend to have high (low) ROE in the future. This is crucial for our research as we are looking for an increase in ROE over three years to form a signal. Finally, Penman highlighted the fact that ROE is better at predicting stock return than that used as a proxy for risk as there is a conflict in the literature regarding the use of the variable. In addition, Ohlson (1995) described stocks prices in terms of ROE.

Recently, Baginski and Wahlen (2003) addressed the question of whether accounting numbers can help to assess firm risk and test whether systematic risk and total volatility in residual income can help to explain the cross section of price differentials. “If price differentials captures the fundamental discount for risk in share prices, and if abnormal return on equity beta or the standard deviation of abnormal return on equity are reliable surrogates for priced risk factors then we expect price differentials to increase with residual income risk” (p. 329, *Residual Income Risk, Intrinsic Values, and Share Prices*). After forming a portfolio, results indicate that volatility in ROE is positively and strongly associated with price differentials. Here we highlight this point to reinforce our view that ROE and stock prices might be linked.

More recently, Ahsan (2012) used ROE to predict stock returns and found that investors can create a portfolio based on ROE. In fact, the study shows that a portfolio based on ROE can generate subsequent returns; however, higher ROE does not signify necessarily higher returns.

Following our discussion on the use of ROE to help explain the cross section in stock returns, Clubb and Naffi (2007) explained the relationship between stock returns and the role of ROE. It is stated in their article: “We note that the identity linking return on equity, stock returns and changes in the book-to-market ratio implies that expected stock returns for a period can be explained by a comparison of expected return on equity and expected change in the book-to-market ratio during the period” (p. 2, *The Usefulness of Book to Market and ROE Expectations for Explaining UK stock Returns*).

Chen and Zhang (2007) suggested that, based on their regression model, on average a ROE increase of 1% will increase stock prices by 0.45% implicitly, implying that stock returns and ROE are positively linked across the whole sample using data over the period 1983 to 2001. Also, the effect differs whether the firm is exhibiting a high level or a low level of profitability. For instance, the authors found that a 1% increase in ROE is associated with a 0.19% increase for low ROE firms. By contrast, Beccalli et al. (2006) suggested that ROE does not help to explain the variation in stock prices.

In summary, the reasoning from these studies is that ROE can be used by investors to predict stock returns as it appears that they are both positively linked.

5.2.4 Portfolio formed on the basis of return on equity (ROE)

A number of empirical studies have compared the benefits of using ROE when forming a portfolio.

For instance, Chen et al. (2011) examined the difference in return between a high ROE portfolio and the return of a low ROE portfolio. They found that profitability ROE is positively associated with return on stocks as such that winners exhibit higher profitability and earn higher expected return than losers.

Also, Branch and Gale (1983), using Compustat data from 1968 to 1981, explored the factors that determine stock prices and particularly examined stock price to profitability and formed the idea that “Companies with low current returns on equity generally have very low price to book P/Bs while those with higher return on equity have higher P/Bs” (p. 4, *Linking Corporate Stock Price Performance to Strategy Formulation*). Likewise, Fairfield (1994) stated that P/B is a function of the expected level of future ROE; in fact, the P/B ratios correlate positively with ROE. The author presents the usefulness of the P/B-ROE valuation model and suggests that this model can anticipate next year’s changes in ROE.

Similarly, Wilcox and Philips (2005) focused on the P/B-ROE approach as an estimation to predict future stock returns. As outlined: “The P/B-ROE model is simple, if its expected return on equity is higher in the first stage than in the second, where it supports an equilibrium price/book ratio, its current P/B must be expected to decline, offsetting its high profitability so as to provide only the required shareholder return. If its expected return on equity is expected to be higher in the second stage, its P/B must be expected to rise until then to supplement its current depressed profitability and achieve the required shareholder return.” (p. 58, *The P/B-ROE Valuation Model Revisited*).

Bagella et al. (2000) analyzed the determinants of cross-sectional stock returns and found that portfolio strategies based on low values of EPS, book to market, market value and on ROE significantly outperform the market. By investigating the UK stock market for the period July 1971 to June 1997, the authors showed astonishing results as their strategies outperformed the benchmark index over 26-year average monthly returns. In this study, return on equity is defined as net profit after tax, minority interests and preference dividends divided by equity capital and reserves minus intangibles plus total deferred tax.

Ahsan (2012) stated that portfolios are able to return subsequent return to investors, and the study shows that portfolios based on ROE can generate subsequent return; however, the author is not able to formulate whether the outperformance occurs more in stocks displaying high ROE or low ROE.

Accordingly, Neuhauser (2013) investigated how investors react to firms' ROE as an investment strategy and hypothesized the idea that investors under-react to ROE information. To do so he designed and assessed a portfolio of high ROE stocks. The author covers the period 1973 to 2004 by investigating the US market. The results show that portfolios formed on the basis of high ROE are able to generate subsequent return even after controlling for Fama and French's (1993) risk factors. The author said: "If investor's under-react to earnings they may under-react to ROE as well since ROE =EPS/BV" (p. 3, *Do Investors Under-React to ROE?*)

Overall, there might be a story when creating a portfolio on the basis of ROE.

5.2.5 Return on equity (ROE) as a momentum strategy

Only a small number of studies have examined the impact of ROE as a momentum strategy. We try in this part to provide support for our strategy.

Figelman (2007) examined the interaction of stock return momentum with various earnings measures, specifically the ROE. The author considered measures such as return on equity, change in ROE and earnings quality. The research was carried out over the period 1970 to 2004 in the S&P 500 universe and analyzed a one-month and six-month holding period when forming portfolios. The author believes that momentum is caused by slow dissemination of news and stipulates: "Slow dissemination of news implies that different investors obtain new information at different times, which causes the stock price to reflect this news only gradually". (p. 71, *Interaction of Stock Returns Momentum with Earnings Measures*).

Additionally, Tziogkidis and Zachouris (2009) examined the performance of variable-orientated momentum strategies. To do so they used 20 variables in the US market over the period 2002 to 2006. Their results suggest that investors can benefit from past trend performance if they take into account firms' specific information. Particularly, they suggest that EPS, low P/E and ROE are variables that contribute the most in producing some good momentum portfolio performances. The authors reported that: "Return on Equity produced relatively large and statistically significant regardless of holding period or momentum" (p. 16, *Momentum Equity Strategies: Are Certain Firm-Specific Variables Crucial in Achieving Superior Performance in Short-term Holding Periods?*), suggesting that momentum strategy on ROE might deliver different returns if they are held in different time windows.

Lee and Swaminathan (2000) found that low turnover winners (losers) have greater (less) momentum, whereas high turnover winners (losers) have less (greater momentum). They also suggested that low turnover stocks have experienced a decline in ROE over the past three years compared with high turnover stocks. In other words, this is expressed by the view that a change in asset turnover is reflected in the change of ROE. As stated: "The pattern is symmetrical: high volume winners have experienced an increase in return on equity whereas low volume winners have experienced an increase in return on equity" (p. 2049, *Price and Trading Volume*).

Finally, Gazmeh et al. (2013) investigated the use of profitability momentum strategy in the Tehran Stock Exchange covering the period 2006 to 2010. Their results suggest that firms that had experienced an increase in ROE in the past three to 12 months may continue to outperform whereas stock unable to increase their ROE may display bad stock returns. The study addressed the importance of using ROE as an investment strategy and considered that ROE can potentially indicate that firms with good past performances in the three to 12 months may continue to outperform firms which had bad performances over the same period for the next three to twelve months.

All the research presented above investigates the claim of some ROE in cross section with stock returns. In general, the authors find that the ROE is exposed to different risk but the question is whether the pattern identified in the ROE is likely to persist over time or the pattern is just another form of survivorship bias. They answer the question by examining different aspects of ROE and, despite the fact that there is not an extensive literature review on the use of ROE as a momentum strategy, we truly believe that this investment idea can be supportive for investors willing to dig into further research.

5.3 Methodology – principles

The stock selection method that we propose in this model is based on the principle that investors should be looking every year for three consecutive increases in a row in return on equity (ROE).

We have decided to collect the data from the Standard & Poor's Compustat North America database which provides fundamentals data on all listed NYSE, Amex and NASDAQ common stocks. The Standard & Poor's North American data is unique in the sense that it is standardized to ensure comparability by removing reporting variability and bias to ensure that comparability exists among similar types of data. Data is collected from shareholders' reports, 10-K reports and other reliable sources. Items include, as an example, annual and quarterly income statement, balance sheet, cash flow data, company name.

When it comes to building the momentum ROE to identify potential winners, we first construct the return on equity variable, which is illustrated as:

$$\boldsymbol{ROE = \frac{Net\ income}{Shareholder's\ equity}}$$

Where Shareholder's equity is calculated as the company's total assets minus total liabilities.

To understand the factors affecting firms' ROE, the literature often refers to DuPont[85] analysis of the return on equity (ROE) ratio, which is displayed in the form:

$$\boldsymbol{ROE = profit\ margin\ X\ Asset\ turnover\ X\ Asset\ leverage}$$

[85] Du Pont model initiated by Du Pont; see for instance Kline and Hissler "The DuPont Chart system for Appraising Operating performance", NACA Bulletin (August 1953).

$$ROE = \frac{Net\ income}{Revenu} x \frac{Revenu}{Assets} x \frac{Assets}{Equity}$$

The DuPont Model was developed in 1919 by a finance executive at E.I. du Pont de Nemours and Co. If ROE is unsatisfactory by some measure, then the DuPont analysis conveys where to start looking for the reasons. For example, if a company's equity value declines sharply, its equity multiplier rises. Thus, in some cases the ROE does not really represent an improvement in financial performance at all.

Profit margin is a useful measure to assess the firm's competitive position; however, this depends merely on the sector as for some companies low margins generates high return. An increase in profit margin will increase the firm's ability to generate funds internally.

Asset turnover is used to measure the operating efficiency of the firm. This ratio is a capital structure/financial leverage ratio indicating the degree to which assets are internally financed. A higher ratio indicates more outstanding financing. The ratio equals one plus the debt/equity ratio where the debt is defined as total liabilities. It indicates the efficiency of the firm's use of assets. An increase in the firm's total asset turnover increases the sales generated for each unit in asset.

Asset leverage measures the financial strategy by giving information of total assets financed by shareholders; when assessing ROE it is important to understand to what extent leverage is used. For instance, if ROE is boosted by leverage therefore investors should consider the risk taken. An increase in the debt-equity ratio increases the firm's financial leverage

Considering the Du Pont analysis, it appears that the ROE could be leveraged up by increasing the amount of debt in the firm. However, increasing debt also increases interest expense, which reduces profit margins and acts to reduce ROE. As well, weakness in operating will show up a diminished return on assets, which will translate into a lower ROE.

In other words, the two factors capable of contributing to an increase in return on equity are an increase in asset turnover and an increase in leverage. Also, companies that create a lot of shareholder equity and deliver high returns are generally self-funding and do not need additional debt or equity investment whereas, if a company's profit margins are shrinking and turnover is slowing, incorporating long-term debt to add some working capital will reverse the declining ROE.

In consequence, ROE reveals how much a company is earning from net assets. Stocks with high debt, low margins and slow rates of asset turnover are said to exhibit higher risk.

By focusing on improving return on equity from one year to another the stock return is likely to increase as earnings grow and margin recovery is taking place. We focus therefore on stocks whose ROE is set to strengthen. After excluding financials using the SIC code provided by Compustat, the model consists of a binary signal, either 1 for a “BUY” or 0 for “no signal”. Table 5.3-1 below provides an example of this.

Table 5.3-1 Momentum strategy

Sector	Company Name	Date	ROE	Signal
Industrial	General Electric CO	31/12/2010	0.099220599	
		31/12/2011	0.110408519	
		31/12/2012	0.114260139	1
Information Technology	Microsoft Corp	30/06/2010	0.406280455	
		30/06/2011	0.405549813	
		30/06/2012	0.25583533	0

Buy as increase during three following years

No signals

5.4 Risk-adjusted performances measures

Higher returns are usually associated with higher risks. In this part we describe in detail measures used to evaluate the strategy such as Information ratio, Jensen Alpha, Maximum drawdown, Treynor ratio and the Sortino ratio.

Jensen Alpha:

The Jensen alpha is a widely used risk-adjusted performance measure that represents the average return of a portfolio in relation to the expected market return, which is based on the CAPM (capital asset pricing model). The higher the alpha, the better the portfolio has performed above the market. The measure was developed by Michael Jensen in 1968 to investigate whether fund managers were able to consistently outperform the market.

Jensen's measure is calculated as:

$$\propto_p = \overline{r_p} - [r_f + \beta_p(\overline{r_m} - r_f)]$$

Where $\overline{r_p}$ is the expected total portfolio return, r_f is the risk-free rate, β_p is the beta of the portfolio and $\overline{r_m}$ is the expected market return.

Information ratio:

The Information ratio is a widely used measure among academicians and practitioners which provides investors with an idea of how the strategy is performing; an annualized Information ratio of 2 means that the strategy is performing well almost every month.

Information ratio is calculated as:

$$Annualized\ Information\ ratio = \frac{R}{\sigma}$$

Where R is the average return obtained from the strategy and σ is the standard deviation of return of the strategy. Both are calculated using the same time frame, in our case 252 trading days.

Sharpe ratio:

The Sharpe ratio is the best-known risk-adjusted return ratio introduced by Sharpe (1966) and differs from the Information ratio by adding a risk-free rate in the numerator.

The Sharpe ratio is a reward to variability ratio and is defined for any portfolio as:

$$Sharpe\ ratio = \frac{R - r}{\sigma}$$

Where R is the expected return on portfolio, σ is the standard deviation of return or the variance of the portfolio and r is the risk-free rate.

The Sharpe ratio measures the slope of the risk-free assets and is widely used to compare alternative strategies such as stock picking or market timing with passive strategies such as tracking the S&P 500 and to compare the performance of different portfolio strategies.

Maximum drawdown:

The maximum drawdown is another indicator of the risk taken by a portfolio. It measures the largest single drop in the value of a portfolio an investor can suffer if s/he enters the market at the worst time. Maximum drawdown is an ex-ante proxy for downside risk that computes the largest drawdown over all intervals of time that can be formed within a specified interval of time.

It is defined as:

$$Min\left[r_t - max\left(\sum_{t=1}^{n} r_t\right)\right]$$

Treynor Index:

The Treynor ratio was first introduced by Treynor (1965) in an attempt to measure how well an investment has compensated its investors given its level of risk. The higher the Treynor ratio the better the performance of the portfolio or stock being analyzed. It is a widely used measure of market-related risk in a stock or collection of stocks.

It is defined as:

$$Treynor\ ratio = \frac{ER_i - r}{\beta_i}$$

It is a measure of the ex-ante excess return per unit of risk but this time the risk is measured by the incremental portfolio risk given by the portfolio-beta. Similar to the Sharpe ratio, the Treynor ratio is used to compare performance of different alternative portfolios and the best portfolio is defined with the highest Treynor ratio.

Sortino ratio:

The Sortino ratio is a modification of the Sharpe ratio in the sense that, instead of considering the general volatility in a portfolio, the Sortino ratio focuses only on the downside volatility. A large Sortino ratio indicates that there is a low chance of a large loss occurring in the portfolio.

It is defined as:

$$Sortino\ Ratio = \frac{R - r}{\sigma_d}$$

Where R is the expected return on portfolio, σ_d is the standard deviation of negative asset return and r is the risk-free rate.

5.5 Empirical results

We start this part by demonstrating how we combine a list of stocks generated by our return on equity (ROE) model and CRSP for stock and market index return information. The code starts by matching our company list with the CRSP Permco[86] identifier using primary issue identifier Linkscore to resolve duplicate links. Then we get daily stock data and add market return. Keeping only common stock identified by CRSP as share code (10, 11), we calculate daily over a one-year period starting 90 days after fiscal period year-end to ensure that the necessary annual financial information is available to investors at the time of portfolio formation; this corresponds roughly to the annual report filing date, expected to be within 90 days of the fiscal period end.

[86] A unique permanent identifier assigned by CRSP to all companies with issues on a CRSP file. This number is permanent for all securities issued by this company regardless of name changes.

Also, returns are calculated including distributions as a value-weighted return. CRSP[87] tracks all securities listed on the NYSE, AMEX, ARCA and NASDAQ exchanges and results were obtained for the period 1991 to 2012.

The objective of this part is to achieve a long portfolio by investing in companies based on our return on equity (ROE) momentum model. To do so we are creating a long portfolio every fiscal year with stocks that have received a 1 as a signal and hold the portfolio over three windows, i.e. a 3-month, 7-month and 12-month horizon for investors willing to benefit from our strategy. For each year our portfolio is constituted of the number of stocks displayed in the table below (see also Appendix G).

Table 5.5-1 Number of stocks every year

Year	No Of Stocks
1992	107
1993	236
1994	278
1995	266
1996	262
1997	330
1998	258
1999	258
2000	289
2001	156
2002	197
2003	311
2004	430
2005	470
2006	409
2007	355
2008	253
2009	119
2010	302
2011	511
2012	308

[87] CRSP provides the date of delisting return and the classification code of the event type. “After a security has been removed from the exchange, CRSP calculate a delisting return of this security by comparing the security’s value after it delists with its price on the last day of trading. The value after delisting can be an off-exchange price, an off-exchange bid-ask spread, or the sum of a series of distribution payments”. In order to avoid biases, incorporating delisting returns would help to assess components of any portfolio more accurately.

The reference benchmark for our long portfolio is the S&P 1500, which is only used for indicative purposes.

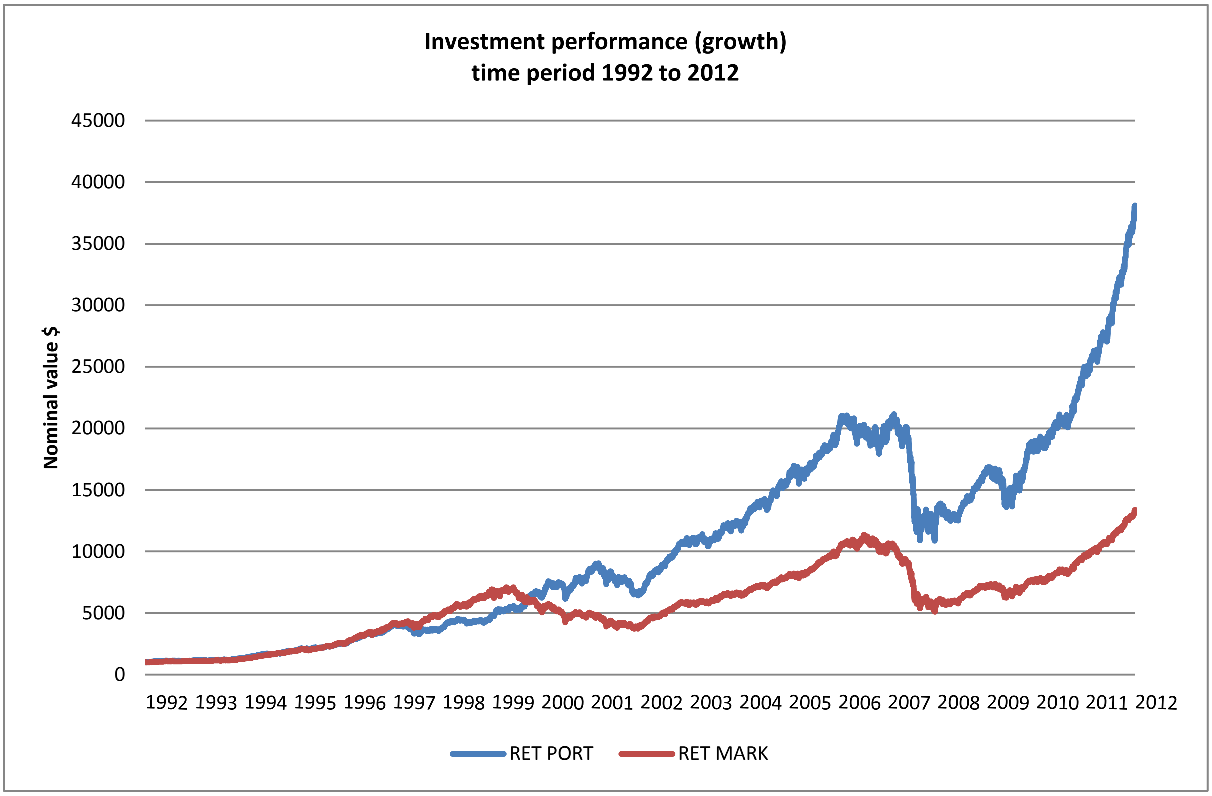

Figure 5.5-1 Investment performance from 1992 to 2012 formulated on a 12-month window

The graph in Figure 5.5-1 above represents the cumulative performance over 21 years in dollars. It shows the value, as of beginning of fiscal year 1992, of a $1,000 investment made on our portfolio when we are holding stocks on a 12-month basis. For comparative purposes, the performance of the S&P 1500 index is used as a benchmark.

We show that the strategy has outperformed the benchmark over the long term, by delivering an alpha investment. This long portfolio has demonstrated skills across the market cycle. This past performances should not be taken as an indication of future performance, which will vary according to market conditions; as we demonstrate later, the strategy appears to underperform during pre-crisis times. Over the past 21 years an investor who invested $1,000 in our portfolio would be worth more or less $40,000.

5.5.1 Excess return

In this part, we describe the excess return obtained when forming a long portfolio. Three time windows are presented, twelve months, seven months and three months.

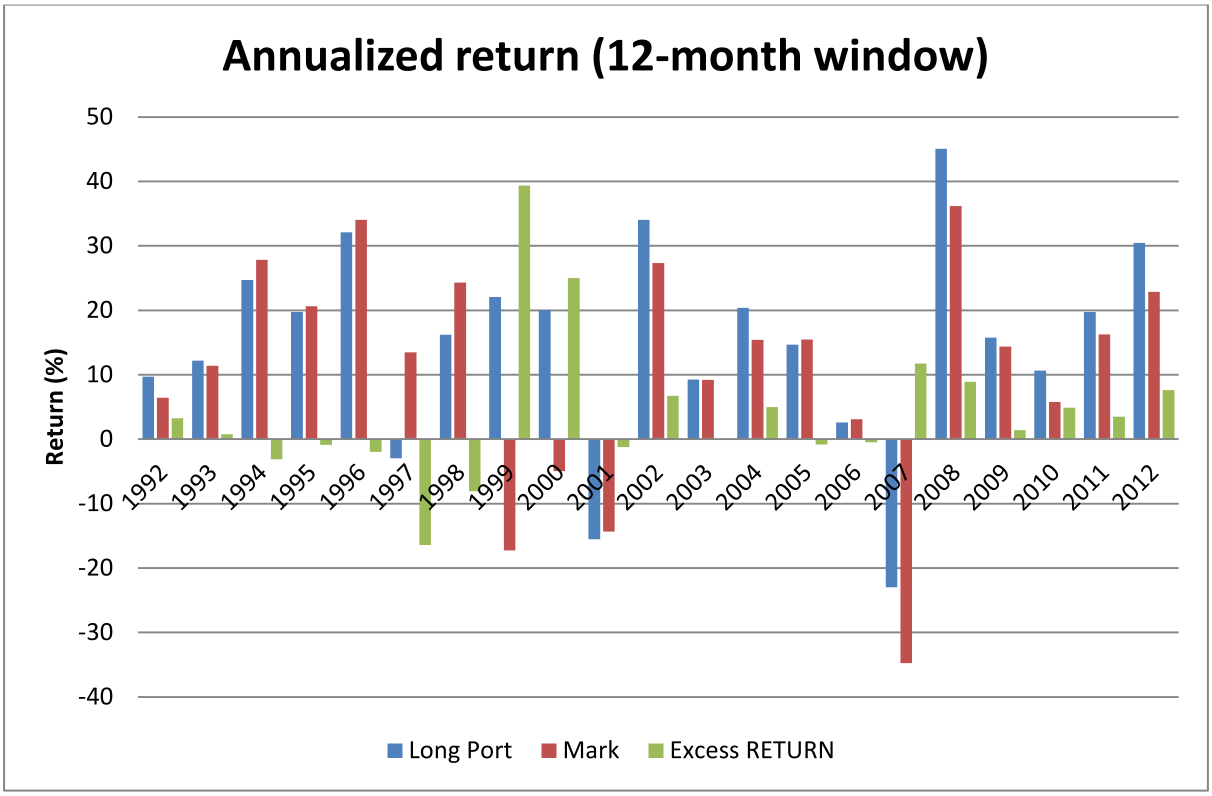

Figure 5.5-2 Long portfolio versus the market across a 12-month window

In Figure 5.5-2, we display the long portfolio annual performance in returns for each fiscal year over the period shown in the chart, i.e. from 1992 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for eight periods out of twenty-one. In other words, this means that investors would have above a 62% chance that we will return money if they were investing in our strategy over a 12-month window.

The strategy performed particularly well in 1999, 2000, 2002 and 2008 with gains of +22.09%, +20.14%, 34.03% and 45.08% respectively compared with -17.27%, -4.98%, 27.31% and 36.19% for the benchmark S&P 1500. In 2012 the strategy has outperformed with 30.46% compared with 22.84% for the benchmark S&P 1500. The excess return earned above the market is about 7.62% on average over 12 months. (Refer to Appendix A.)

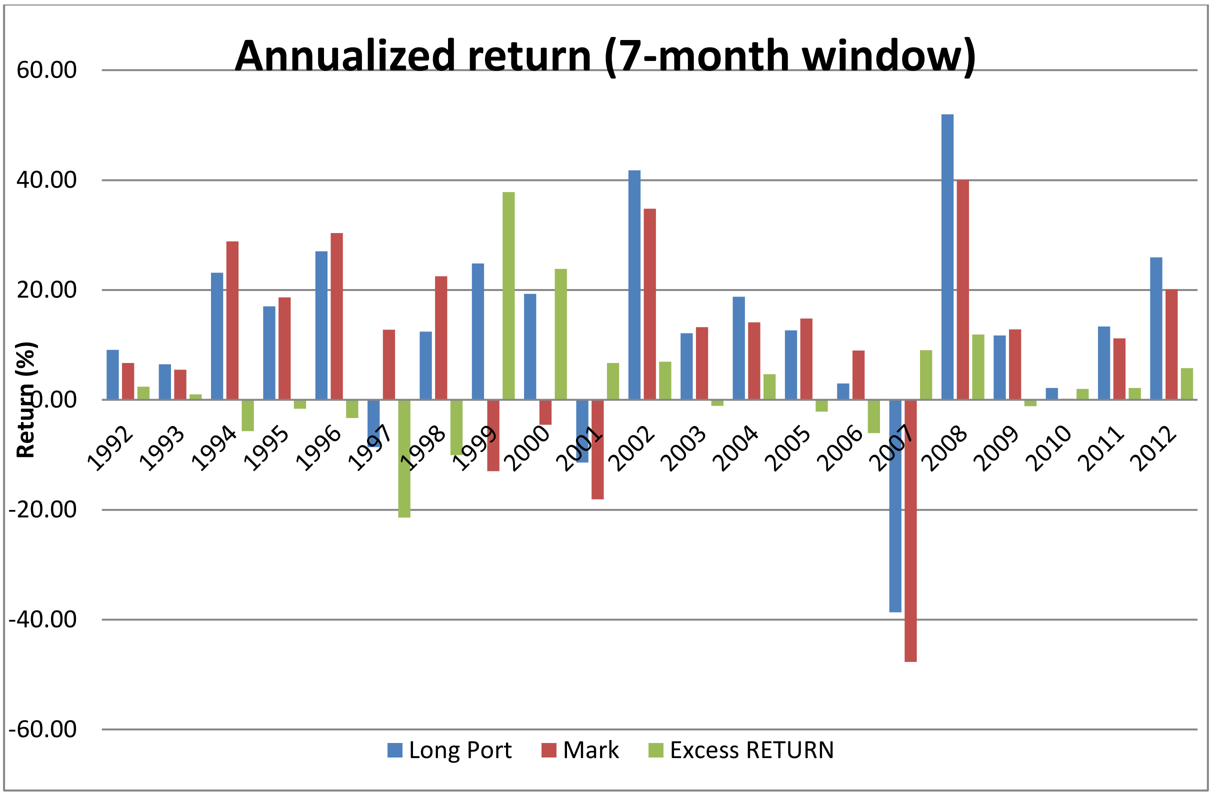

Figure 5.5-3 Long portfolio versus the market across a 7-month window

In Figure 5.5-3 we display the long-short portfolio 7-month annualized performance in returns for each fiscal year over the period shown in the chart, i.e. from 1992 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for nine periods out of twenty-one. In other words, this means that investors would have above a 57% chance that we will return money if they were investing in our strategy over a 7-month window.

The strategy performed particularly well in 1999, 2000, 2002 and 2008 with gains of +24.86%, +19.29%, 41.80% and 51.97% respectively compared with -12.86%, -4.55%, 34.82% and 40.04% for the benchmark S&P 1500. In 2012 the strategy has outperformed with 25.93% compared with 20.13% for the benchmark S&P 1500. The excess return earned above the market is about 5.80% on average over seven months. (Refer to Appendix A.)

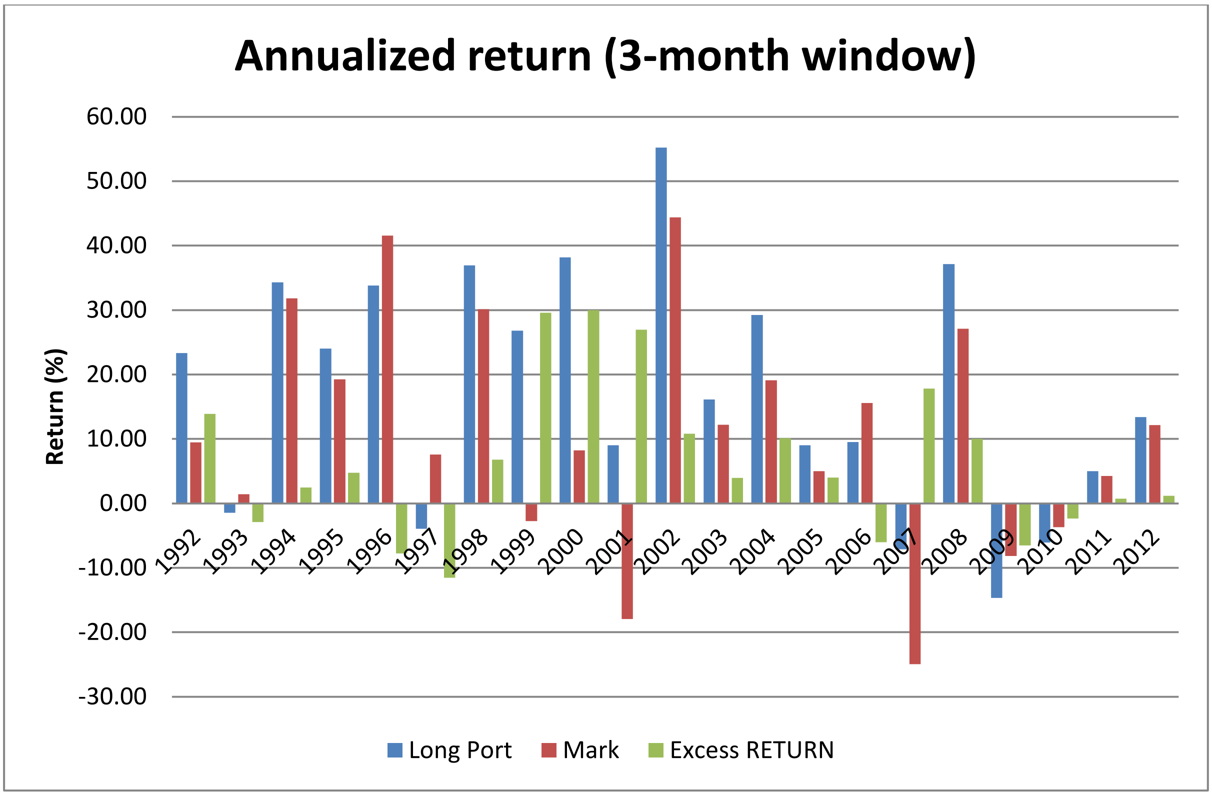

Figure 5.5-4 Long portfolio versus the market across a 3-month window

In Figure 5.5-4 we display the long-short portfolio 3-month annualized performance in returns for each fiscal year over the period shown in the chart, i.e. from 1992 to 2012. It is expressed as a percentage. Here the S&P 1500 is used as a benchmark which is reflected in the chart in red. The chart shows as well that, during the period on display, the strategy is not returning positive excess returns to investors for six periods out of twenty-one. In other words, this means that investors would have above a 71% chance that we will return money if they were investing in our strategy over a 3-month window.

This suggests that perhaps the best investment horizon might be three months as we have the chance to deliver excess returns.

The strategy performed particularly well in 1999, 2000, 2002 and 2008 with gains of +26.82%, +38.20%, 55.23% and 37.12% respectively compared with -2.76%, -8.23%, 44.40% and 27.13% for the benchmark S&P 1500. In 2012 the strategy has outperformed with 13.37% compared with 12.17% for the benchmark S&P 1500. The excess return earned above the market is about 1.20% on average over three months. (Refer to Appendix A.)

5.5.2 Drawdown

In this part, we present the maximum drawdown over the different time horizons.

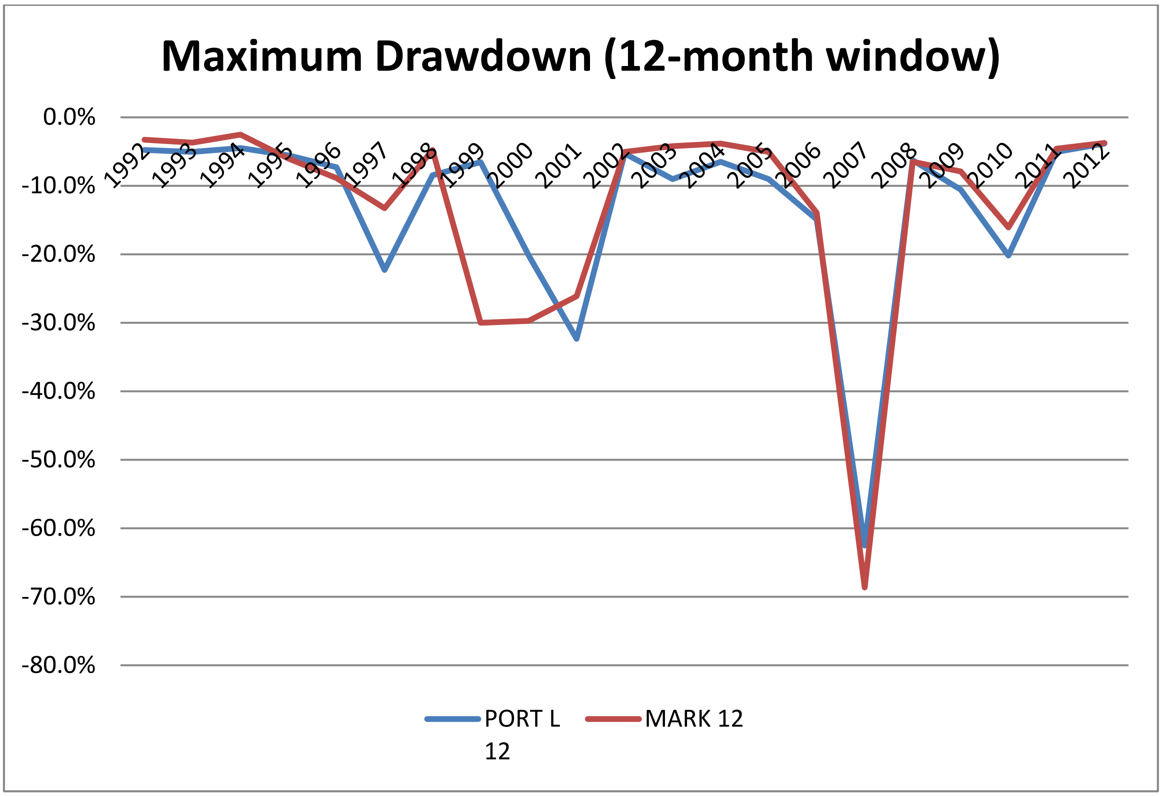

Figure 5.5-5 Maximum drawdown (12-month window)

In Figure 5.5-5, we present the maximum drawdown of our strategy over a 12-month horizon window for the period 1992 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -62.5% in 2007 compared to -68.7% for the benchmark, here the S&P 1500, which is identified in the chart by “MARK 12”. Therefore, even during crisis times our strategy is less risky.

The second largest drawdown of our strategy occurs in 2001 with a drawdown of -32.4% compared to the benchmark of -26.1% the same year. The third largest drawdown is in 1997: -22.3% compared to -13.3% respectively for the benchmark. (Refer to Appendix B.)

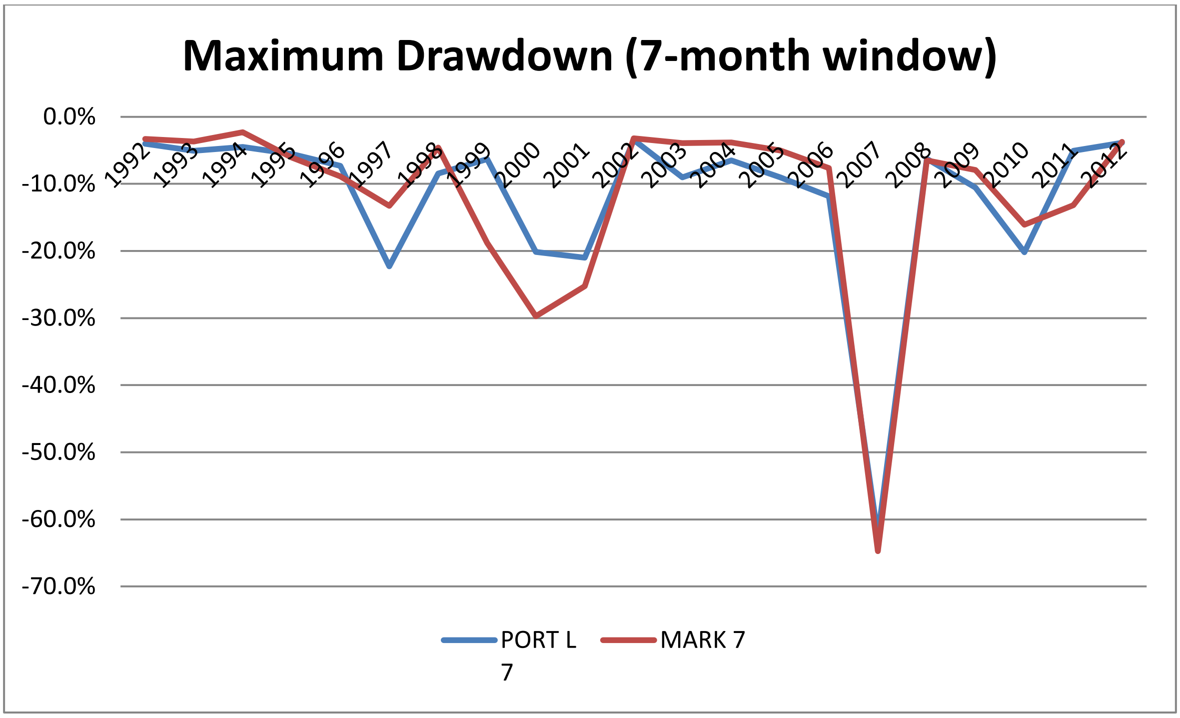

Figure 5.5-6 Maximum drawdown (7-month window)

In Figure 5.5-6, we present the maximum drawdown of our strategy over a 7-month horizon window for the period 1992 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -62.5% in 2007 compared to -64.8% for the benchmark, here the S&P 1500, which is identified in the chart by “MARK 7”. The second largest drawdown of our strategy occurs in 1997 with a drawdown of -22.3% compared to the benchmark of -13.3% the same year. The third largest drawdown is in 2001: -21.0% compared to -25.2% respectively for the benchmark. (Refer to Appendix B.)

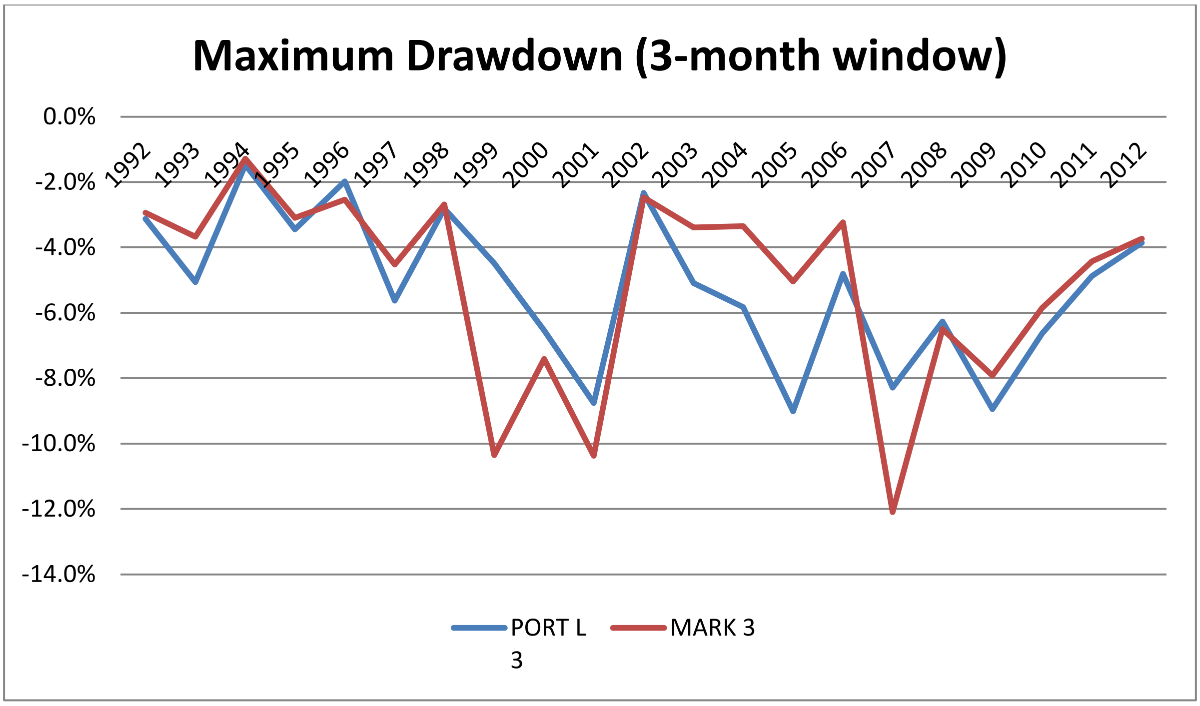

Figure 5.5-7 Maximum drawdown (3-month window)

In Figure 5.5-7, we present the maximum drawdown of our strategy over a 3-month horizon window for the period 1992 to 2012. Maximum drawdown is by definition the maximum percentage loss. The worst drawdown for our portfolio is -9.0% in 2005 compared to -5.0% for the benchmark, here the S&P 1500, which is identified in the chart by "MARK 3". The second largest drawdown of our strategy occurs in 2009 with a drawdown of -8.9% compared to the benchmark of -7.9% the same year. The third largest drawdown is in 2001: -8.8% compared to -10.4% respectively for the benchmark.

To some extent as the maximum drawdown occurs gradually we would have been able to leave the strategy at this point in time in order to limit the downside risk. (Refer to Appendix B.)

5.5.3 Beta

In this part, we describe beta over the different time horizons.

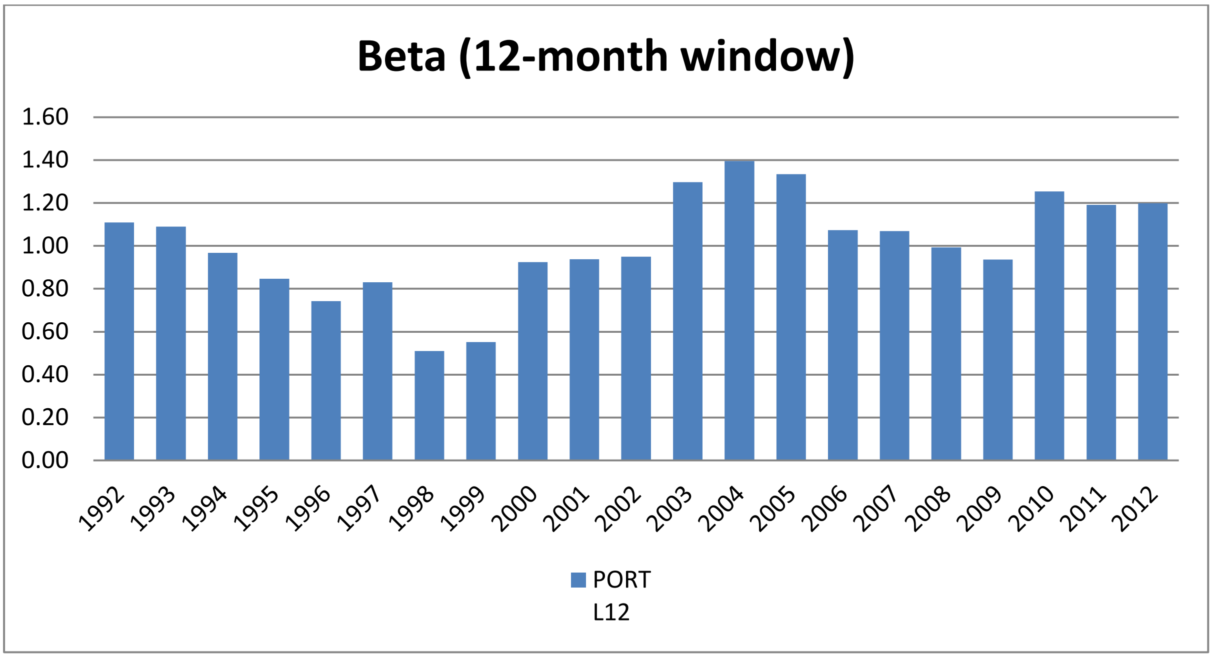

Figure 5.5-8 Beta (12-month window)

In the above chart in Figure 5.5-8 we present beta computed for a 12-month horizon window for our long portfolio, which is denoted in "blue".

By definition beta is the measurement of volatility of a portfolio in relation to the market. A portfolio with a beta of one will tend to move in line with the market; by contrast, a portfolio with a beta higher than one will be more volatile; inversely, a portfolio with a beta of less than one will be less volatile than the market.

For example, in 2010 the beta on the long portfolio of 1.25 shows that the portfolio has performed 25% better than the benchmark, here the S&P 1500. The reverse if the market is falling. By contrast, in 1998 the beta on the long portfolio of 0.51 shows that the portfolio is expected to perform 49% worse than the market during up markets and 49% better during down markets.

Long portfolio managers are looking to generate higher market-adjusted return. As an illustration, in 2011 we manage to get a 3.47% excess return with a beta of 1.19. In 2007, we manage to get an excess return of 11.76% with a beta of 7%, suggesting that this year we manage to generate higher alpha or also better risk-adjusted return than in 2011. (Refer to Appendix C.)

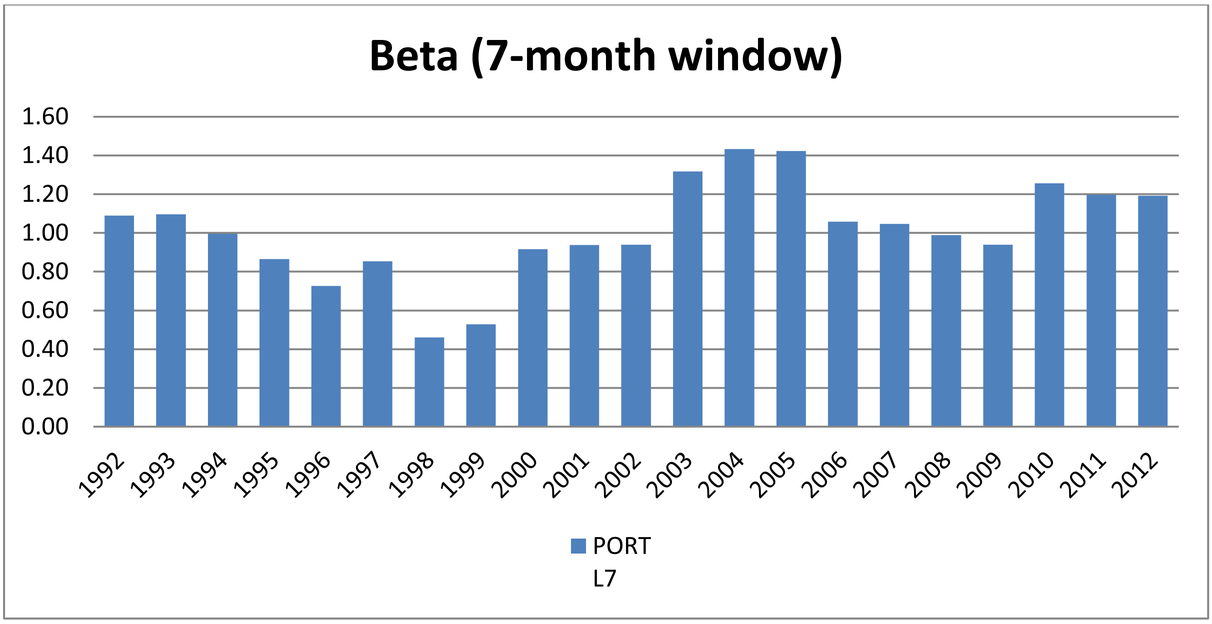

Figure 5.5-9 Beta (7-month window)

In the chart above in Figure 5.5-9 we present beta computed for a 7-month horizon window for our long portfolio, which is denoted in "blue".

For example, in 2010 the beta on the long portfolio of 1.26 shows that the portfolio has performed 26% better than the benchmark, here the S&P 1500. The reverse if the market is falling. By contrast, in 1998 the beta on the long portfolio of 0.46 shows that the portfolio is expected to perform 54% worse than the market during up markets and 54% better during down markets.

Long portfolio managers are looking to generate higher market-adjusted return. As an illustration, in 2011 we manage to get 2.16% excess return with a beta of 20%. In 2007, we manage to get an excess return of 9.03% with a beta of 5%, suggesting that this year we manage to generate higher alpha or also better risk-adjusted return than in 2011. (Refer to Appendix C.)

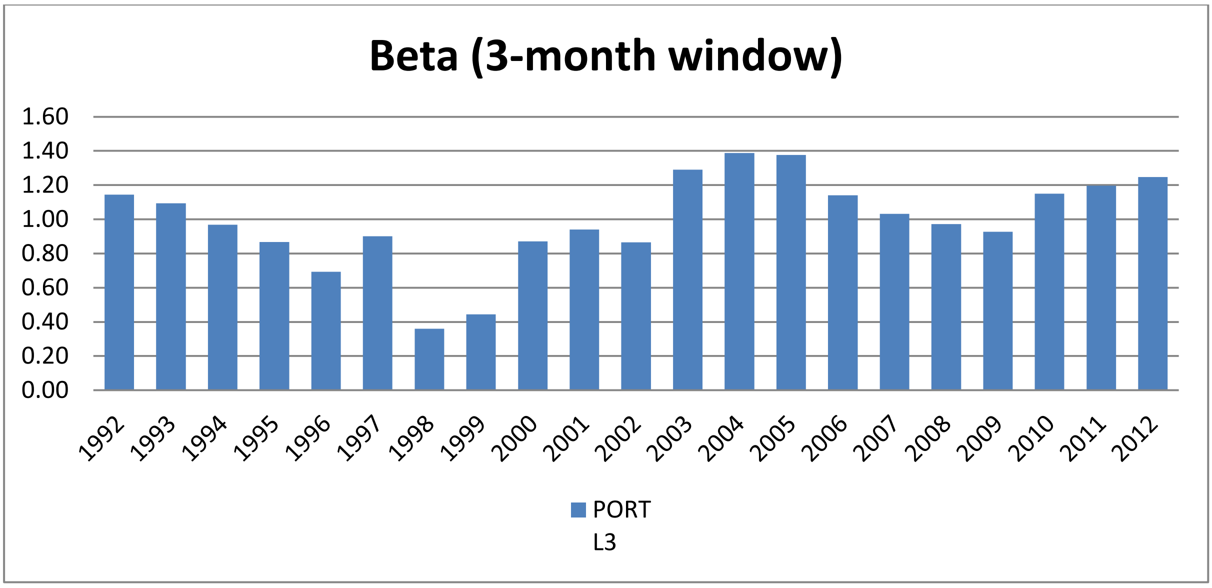

Figure 5.5-10 Beta (3-month window)

In the chart above in Figure 5.5-10 we present beta computed for a 3-month horizon window for our long portfolio, which is denoted in "blue".

For example, in 2010 the beta on the long portfolio of 1.15 shows that the portfolio has performed 15% better than the benchmark, here the S&P 1500. The reverse if the market is falling. By contrast, in 1998 the beta on the long portfolio of 0.36 shows that the portfolio is expected to perform 64% worse than the market during up markets and 64% better during down markets.

Long portfolio managers are looking to generate higher market-adjusted return. As an illustration, in 2011 we manage to get 0.72% excess return with a beta of 20%. In 2007, we manage to get an excess return of 17.83% with a beta of 3%, suggesting that this year we manage to generate higher alpha or also better risk-adjusted return than in 2011. (Refer to Appendix C.)

5.5.4 Sharpe ratio/ Information ratio/ Sortino ratio/ Treynor ratio/ Jensen's alpha

In this part, we analyze the different ratios over the different time horizons.

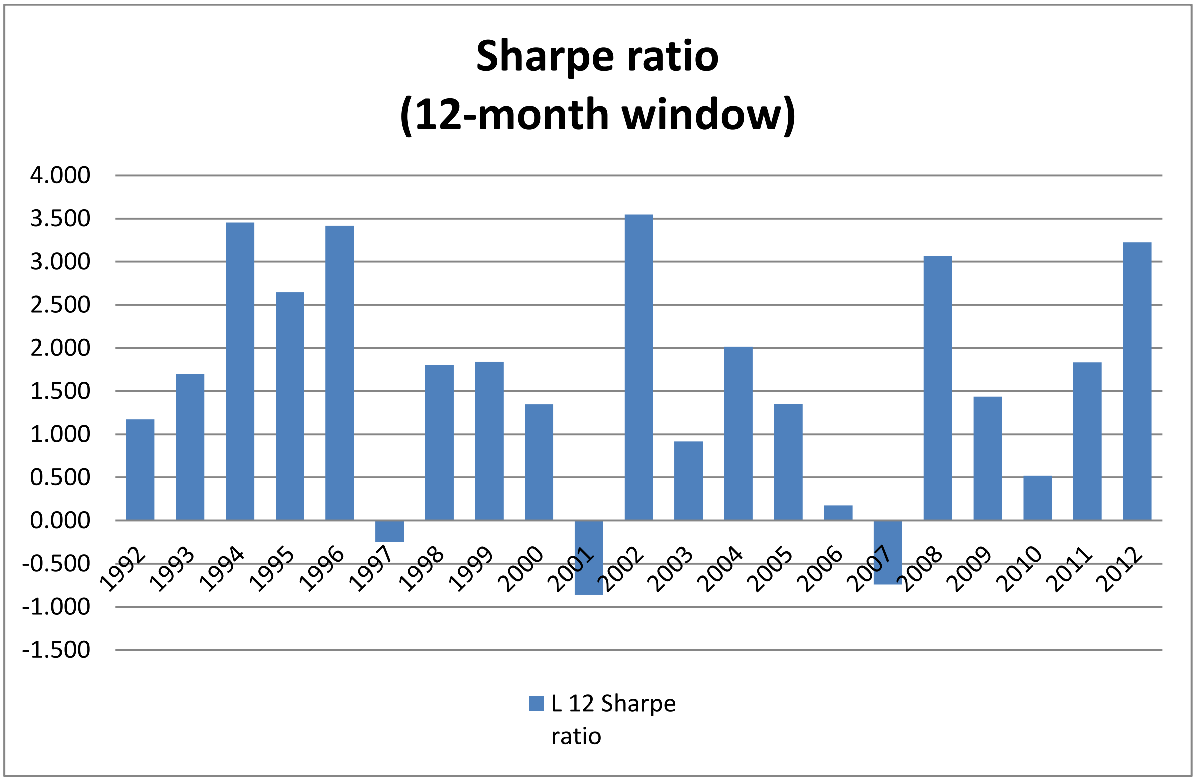

Figure 5.5-11 Sharpe ratio (12-month window)

In Figure 5.5-11, the Sharpe ratio is used to express how much return is achieved for the amount of risk taken in an investment; when interpreting Sharpe ratio investors look at the highest one as the higher the ratio the better the fund.

As an illustration, Figure 5.5-12 shows the Sharpe ratios calculated for our long portfolio over the different years on a 12-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 3.225% per annum per unit of volatility, which corresponds to a Sharpe ratio of 3.225; by contrast, a Sharpe ratio below 1 as identified in 2010 (0.520) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional for the risk taken as, for example, in 1992 (1.172). In this chart, the Sharpe ratio ranges from -0.860 in 2001 to 3.547 in 2002. The mean and the median are both around 1.65. (Refer to Appendix D.)

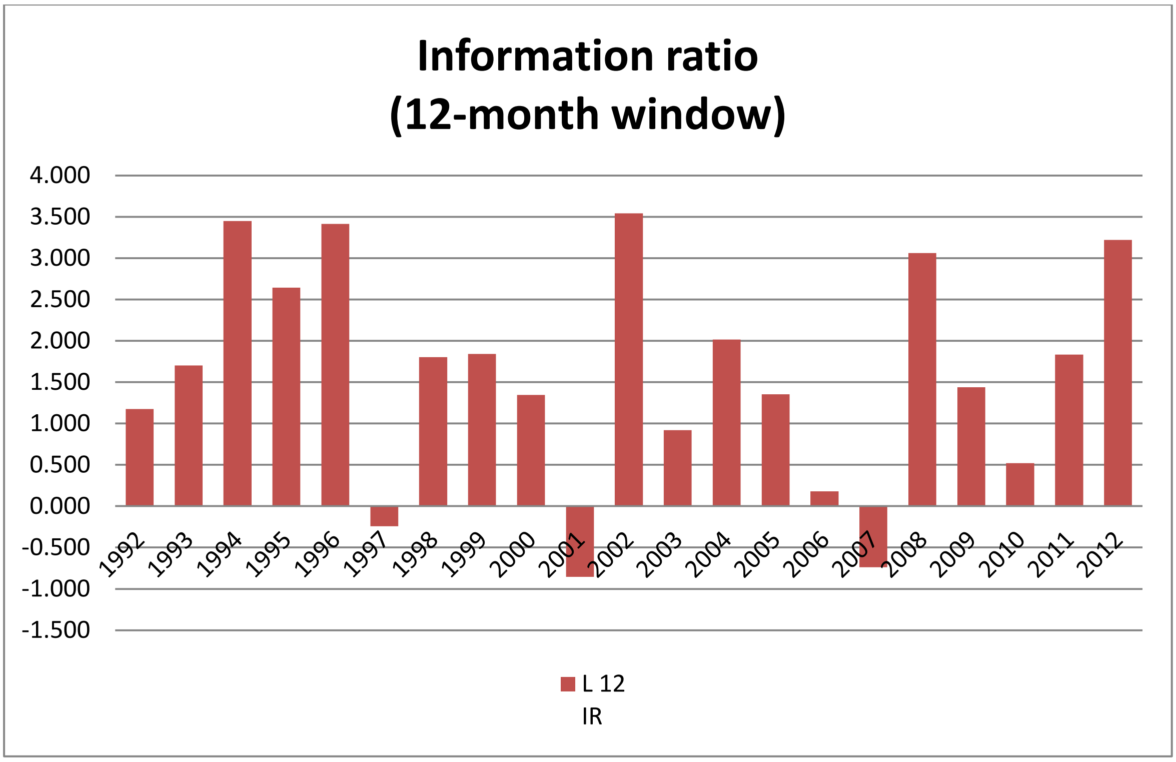

Figure 5.5-12 Information ratio (12-month window)

Figure 5.5-12 shows the Information ratio, which is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using the same investment style, the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -0.738, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -0.854 in 2001 to 3.542 in 2002. The mean and the median are both around 1.65. (Refer to Appendix D.)

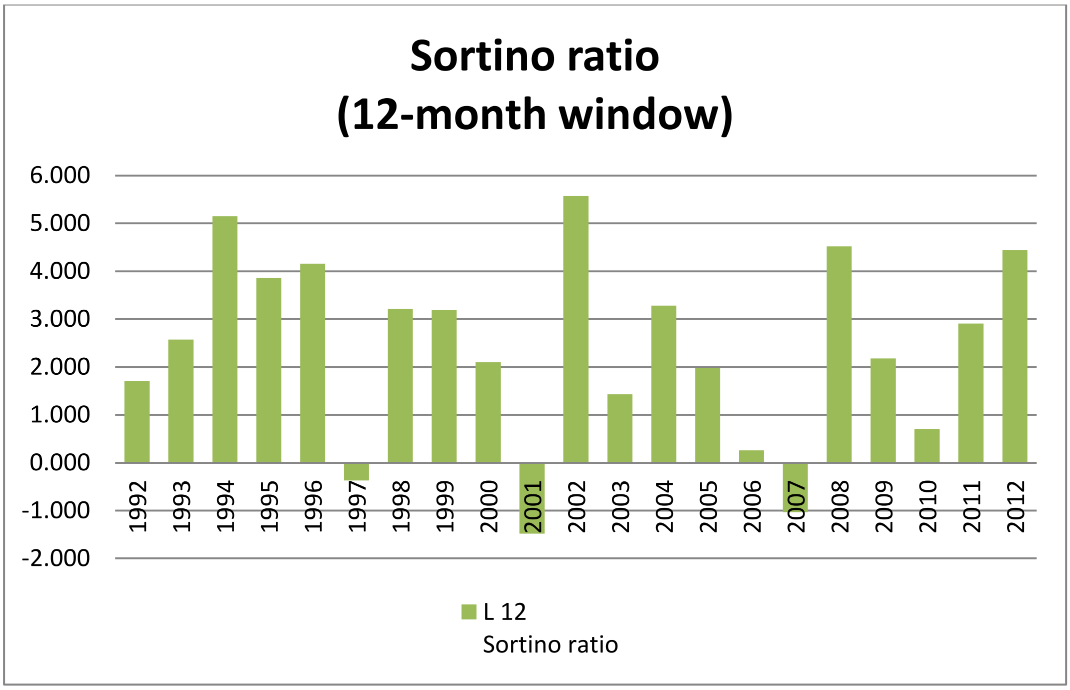

Figure 5.5-13 The Sortino ratio (12-month window)

In Figure 5.5-13, the Sortino ratio, which replaces the volatility in the Sharpe ratio with a measure of downside deviations, confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -1.483 in 2001 to 5.573 in 2002. The mean and the median are both around 2.4. (Refer to Appendix D.)

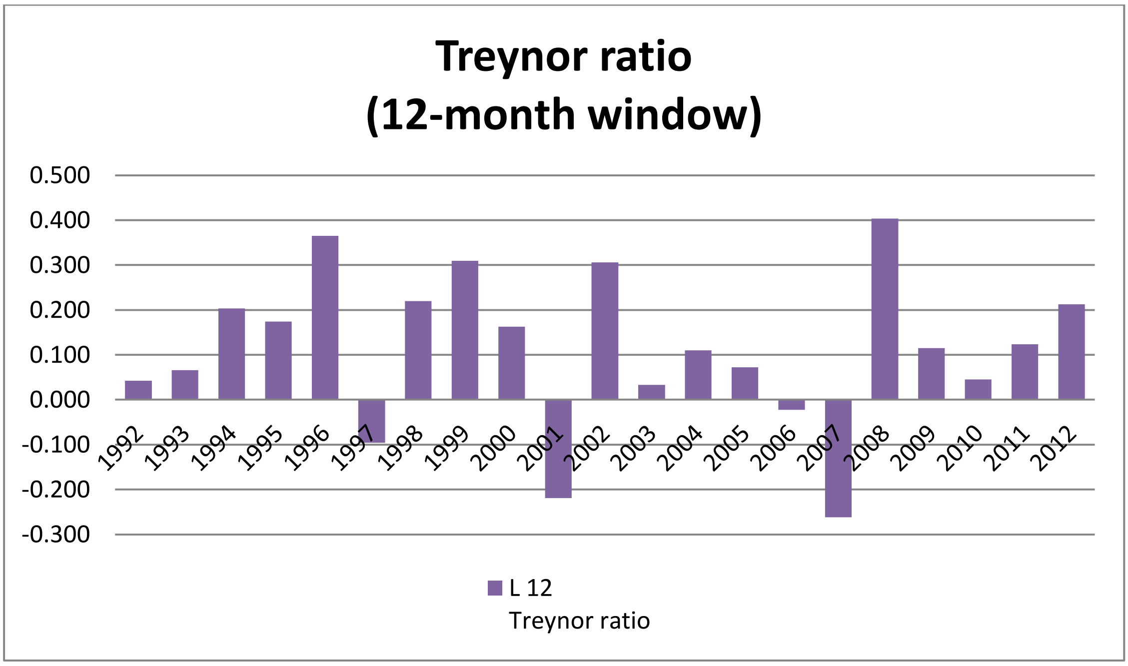

Figure 5.5-14 Treynor Ratio (12-month window)

In Figure 5.5-14, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar returns. In this chart, the Treynor ratio ranges from -0.262 in 2007 to 0.404 in 2008. The mean and the median are both around 0.130. (Refer to Appendix D.)

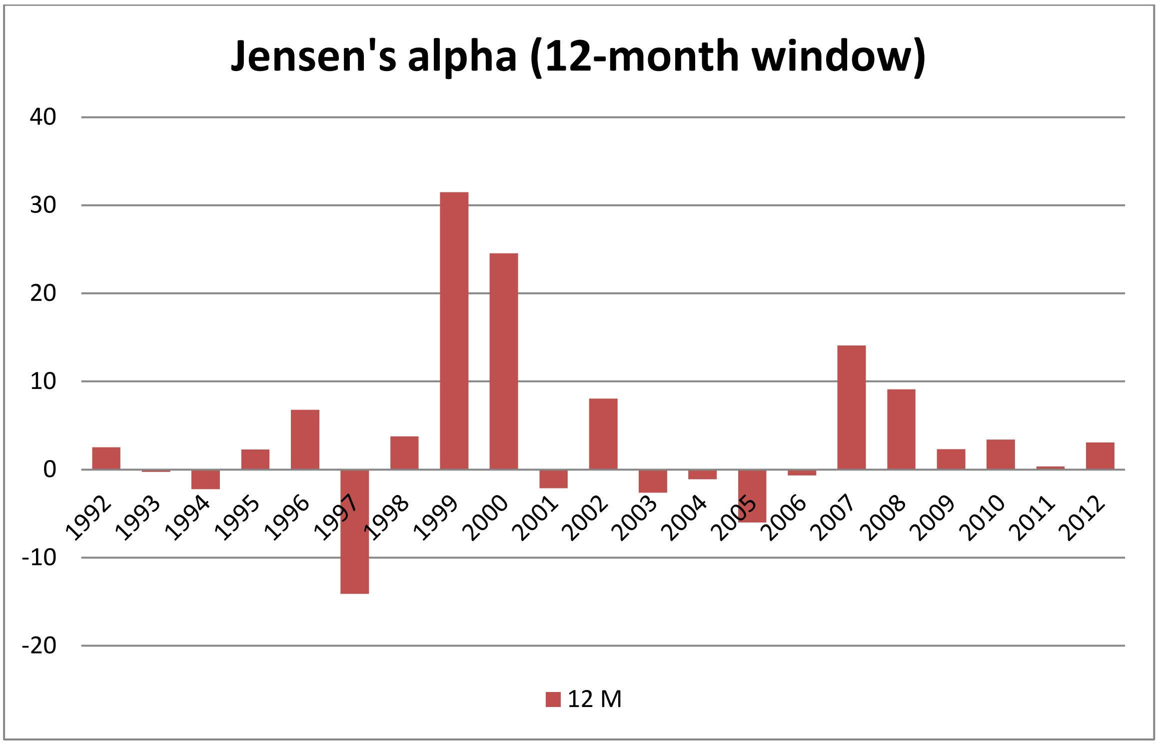

Figure 5.5-15 Jensen's alpha (12-month window)

Figure 5.5-15 shows Jensen's alpha, which is another risk-adjusted measure, confirming the superiority of our strategy in delivering positive alpha over the years. In this chart, the Jensen's alphas range from 31.50 to -14.11. The mean and the median are 2.30 (3.93) respectively. (Refer to Appendix D.)

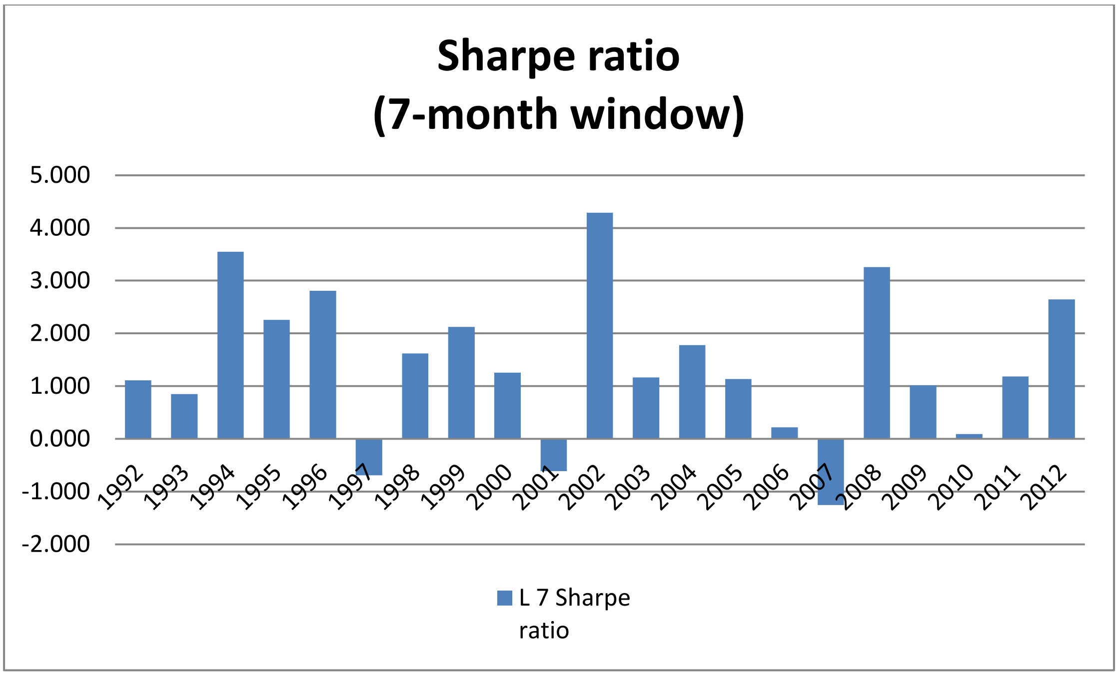

Figure 5.5-15 Sharpe ratio (7-month window)

As an illustration, Figure 5.5-16 shows the Sharpe ratios calculated for our long portfolio over the different years on a 7-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 2.646% per annum per unit of volatility, which corresponds to a Sharpe ratio of 2.646; by contrast, a Sharpe ratio below 1 as identified in 2006 (0.175) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional for the risk taken as, for example, in 2005 (1.352). In this chart, the Sharpe ratio ranges from -1.257 in 2007 to 4.287 in 2002. The mean and the median are both around 1.2. (Refer to Appendix D.)

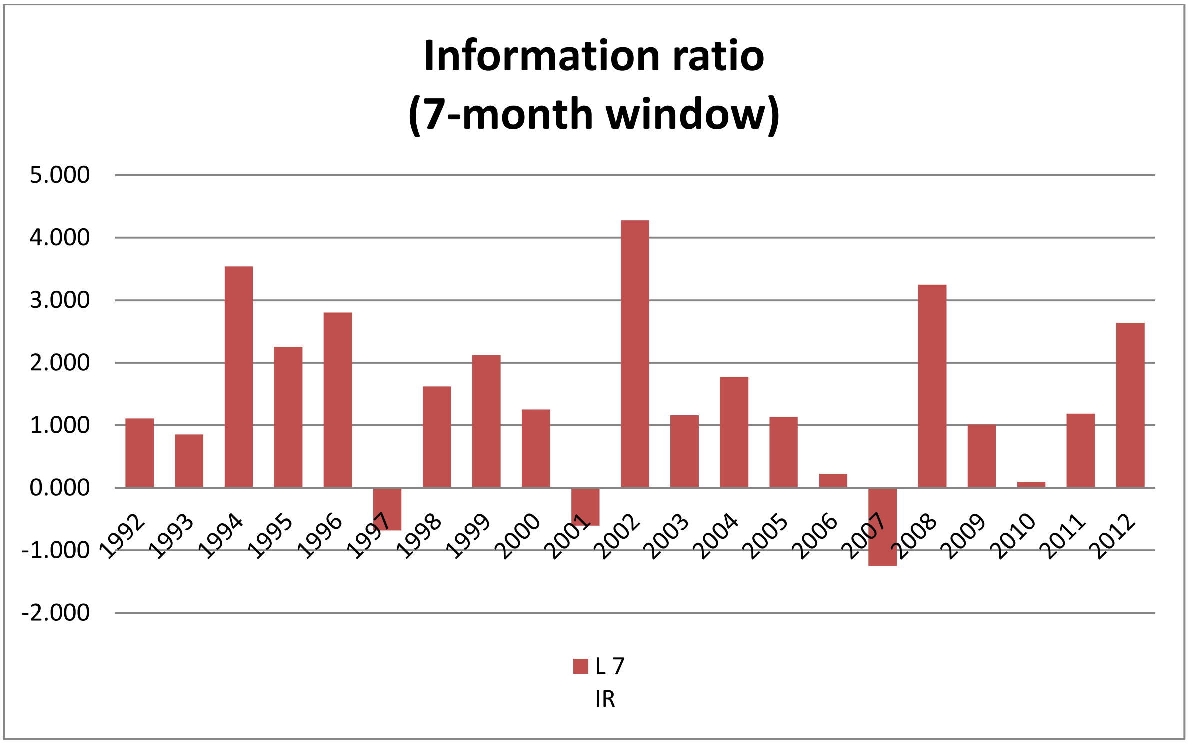

Figure 5.5-16 Information ratio (7-month window)

Figure 5.5-17 shows the Information ratio, which is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using the same investment style the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -1.251, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -1.251 in 2007 to 4.276 in 2002. The mean and the median are both around 1.2. (Refer to Appendix D.)

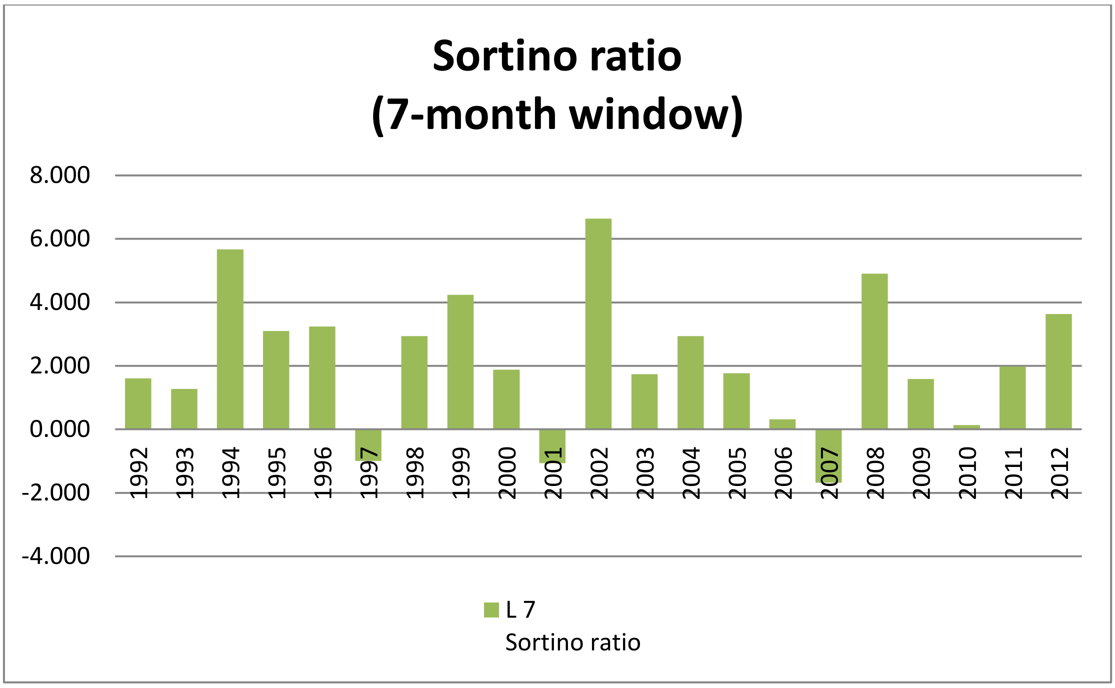

Figure 5.5-17 Sortino ratio (7-month window)

In Figure 5.5-18, the Sortino ratio, which replaces the volatility in the Sharpe ratio with a measure of downside deviations, confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -1.683 in 2007 to 6.638 in 2002. The mean and the median are both around 2. (Refer to Appendix D.)

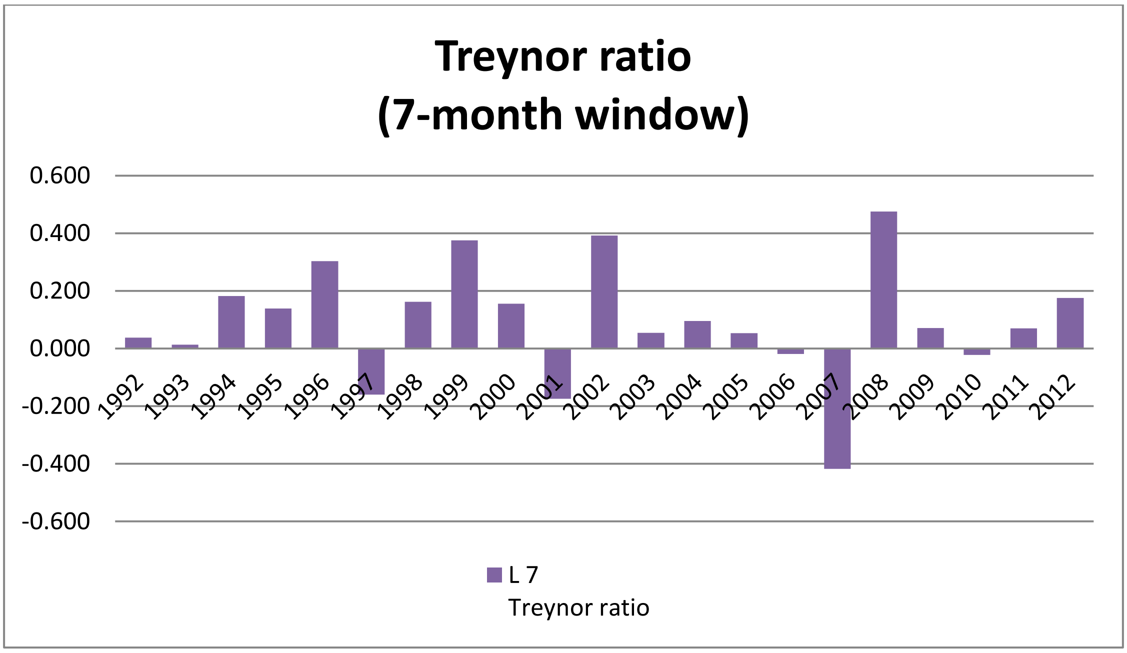

Figure 5.5-19 Treynor ratio (7-month window)

Finally, in Figure 5.5-19, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar return. In this chart, the Treynor ratio ranges from -0.417 in 2007 to 0.475 in 2008. The mean and the median are both around 0.080. (Refer to Appendix D.)

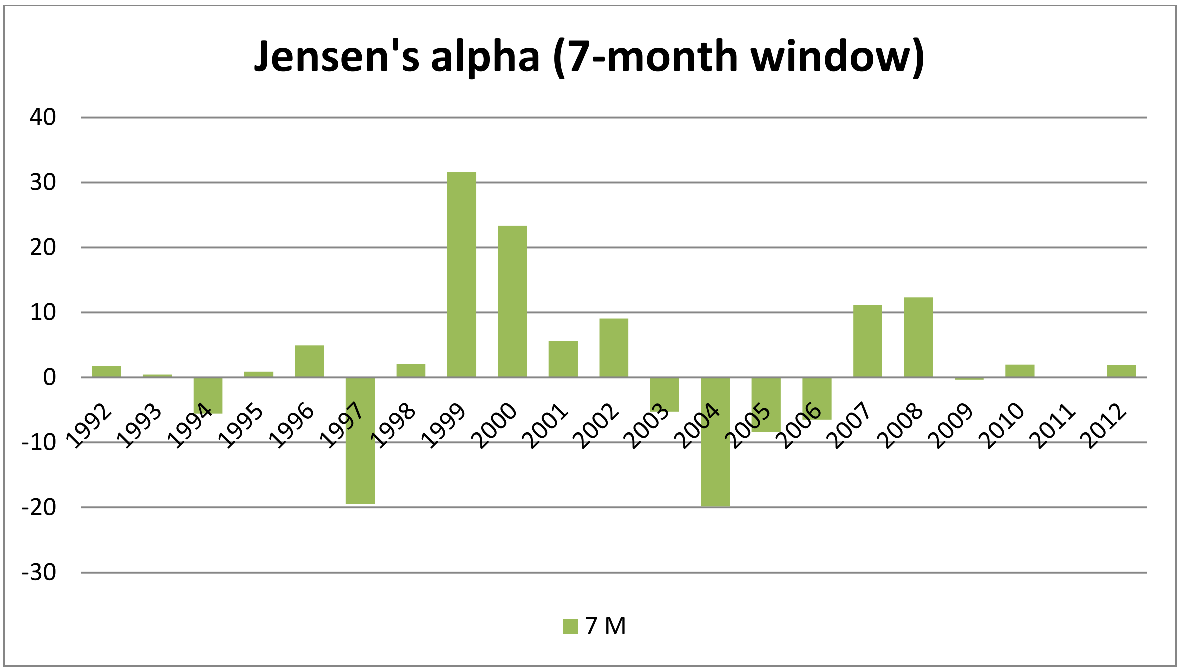

Figure 5.5-18 Jensen's alpha (7-month window)

In Figure 5.5-20, Jensen's alpha is another risk-adjusted measure confirming the superiority of our strategy in delivering positive alpha over the years. In this chart, the Jensen's alphas range from 31.57 to -19.84. The mean and the median are 1.79 (1.98) respectively. (Refer to Appendix D.)

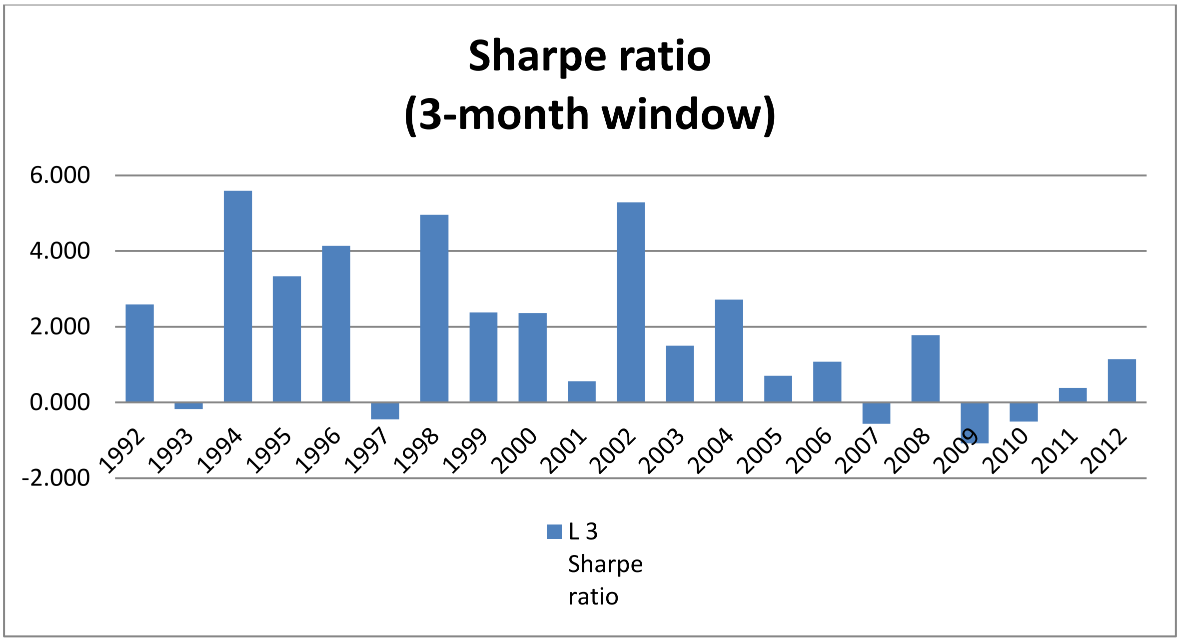

Figure 5.5-19 Sharpe ratio (3-month window)

In Figure 5.5-21, we present the Sharpe ratios calculated for our long portfolio over the different years on a 3-month annualized window. For demonstration purposes, in 2012 the portfolio is offering a reward of 1.143% per annum per unit of volatility, which corresponds to a Sharpe ratio of 1.143; by contrast, a Sharpe ratio below 1 as identified in 2005 (0.699) indicates a return on investment that is less than the risk taken. Also, a Sharpe ratio just above 1 will indicate a return proportional for the risk taken as, for example, in 2003 (1.499). In this chart, the Sharpe ratio ranges from -1.084 in 2009 to 5.595 in 1994. The mean and the median are both around 1.6. (Refer to Appendix D.)

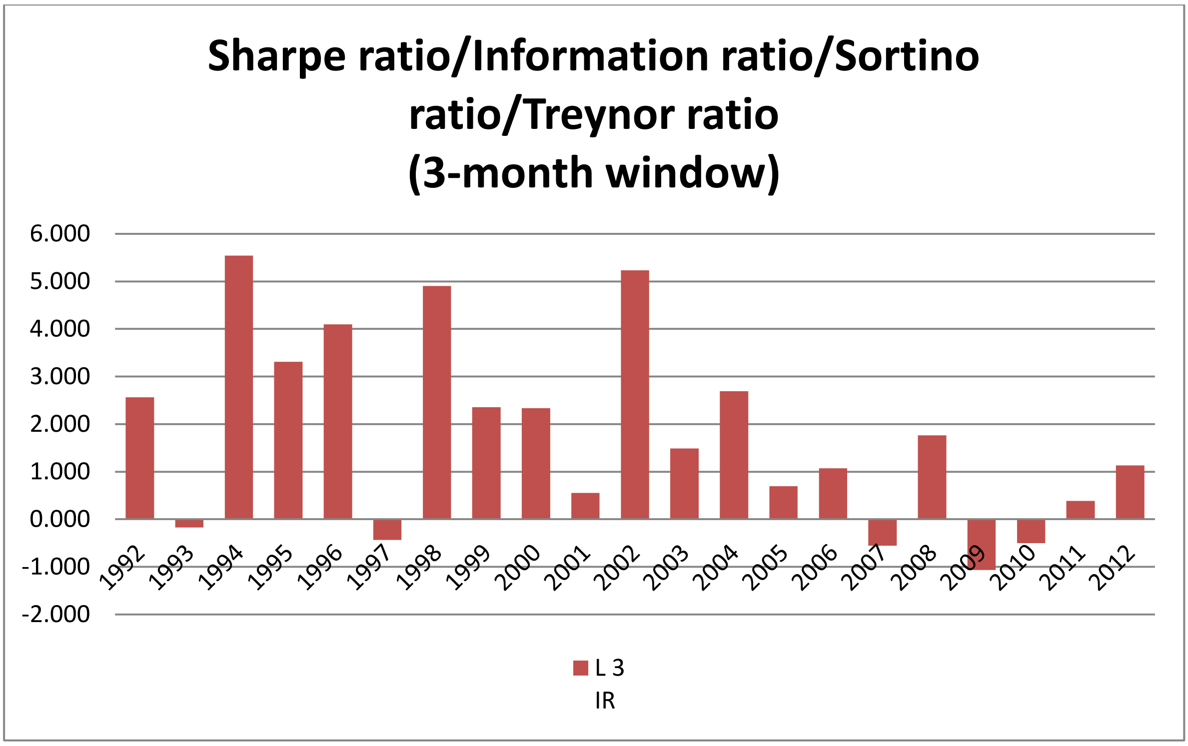

Figure 5.5-20 Information ratio (3-month window)

Figure 5.5-22 shows the Information ratio, which is another measure of risk; it indicates how successful the portfolio has been at taking risk relative to the benchmark. When comparing funds using same investment style the Information ratio is a useful approach to identify a manager who has been more efficient at picking stocks. For example, in 2007 the Information ratio is negative, -0.554, highlighting our poor ability during crisis times to identify good stocks. In this chart, the Information ratio ranges from -1.068 in 2009 to 5.541 in 1994. The mean and the median are both around 1.5. (Refer to Appendix D.)

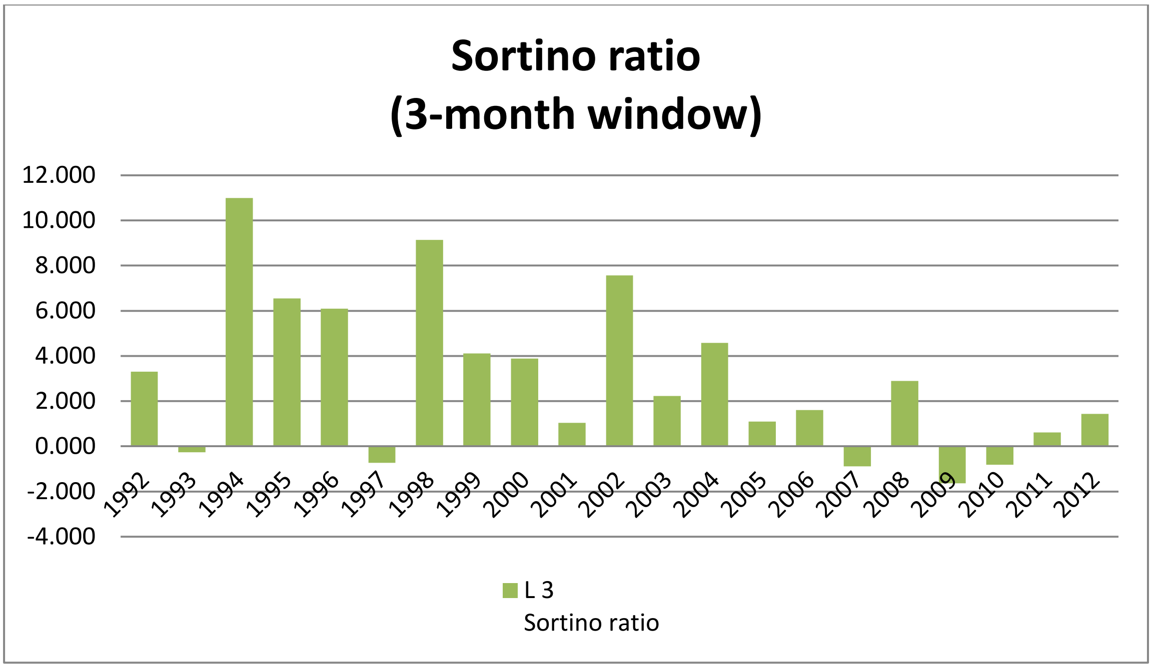

Figure 5.5-21 Sortino ratio (3-month window)

In Figure 5.5-23, the Sortino ratio, which replaces the volatility in the Sharpe ratio with a measure of downside deviations, confirms the superiority of our strategy over the different years. In this chart, the Sortino ratio ranges from -1.635 in 2009 to 10.986 in 1994. The mean and the median are both around 2.5. (Refer to Appendix D.)

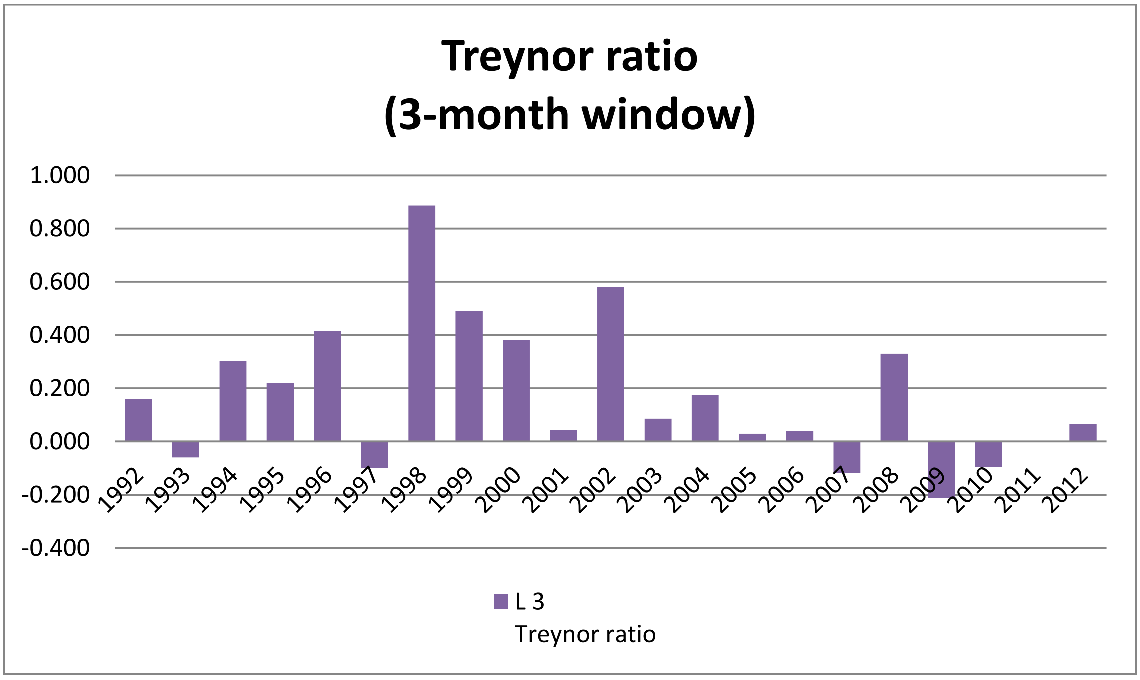

Figure 5.5-22 Treynor ratio (3-month window)

In Figure 5.5-24, the Treynor ratio measures the efficiency of a portfolio per unit of risk using beta as the measure of risk; a higher Treynor ratio means a better risk-adjusted return. It is useful in comparing portfolios that invest in similar market sectors and achieve similar return. In this chart, the Treynor ratio ranges from -0.213 in 2009 to 0.887 in 1998. The mean and the median are both around 0.140. (Refer to Appendix D.)

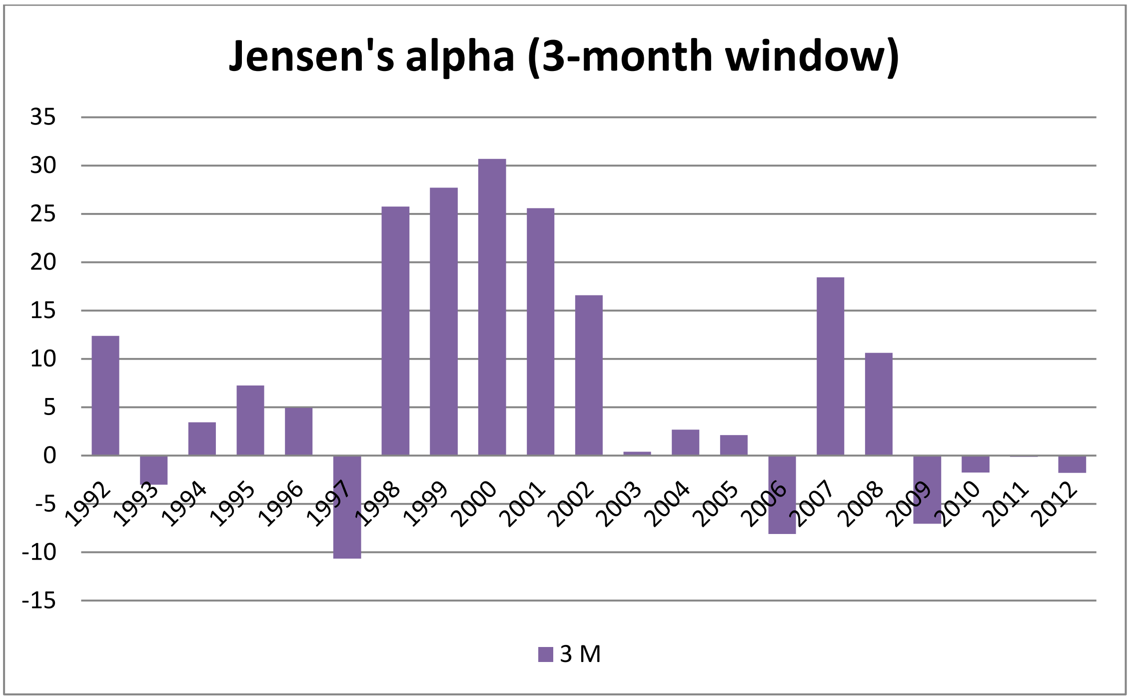

Figure 5.5-23 Jensen’s alpha (3-month window)

In Figure 5.5-25, Jensen’s alpha is another risk-adjusted measure confirming the superiority of our strategy in delivering positive alpha over the years. In this chart, the Jensen’s alphas range from 30.68 to -19.84. The mean and the median are 3.44 (7.43) respectively. (Refer to Appendix D.)

5.5.5 Correlation

In this part, we present a chart and a summary results table obtained for the correlation of our long portfolio against the market.

Correlation is a useful metric when measuring how the returns of two investments move in relation to each other; we display below a chart on a 3-month window with the correlation for the long portfolio. The results display a symmetrical correlation for both long and short portfolio. The same can be observed on a 7-month or a 12-month window.

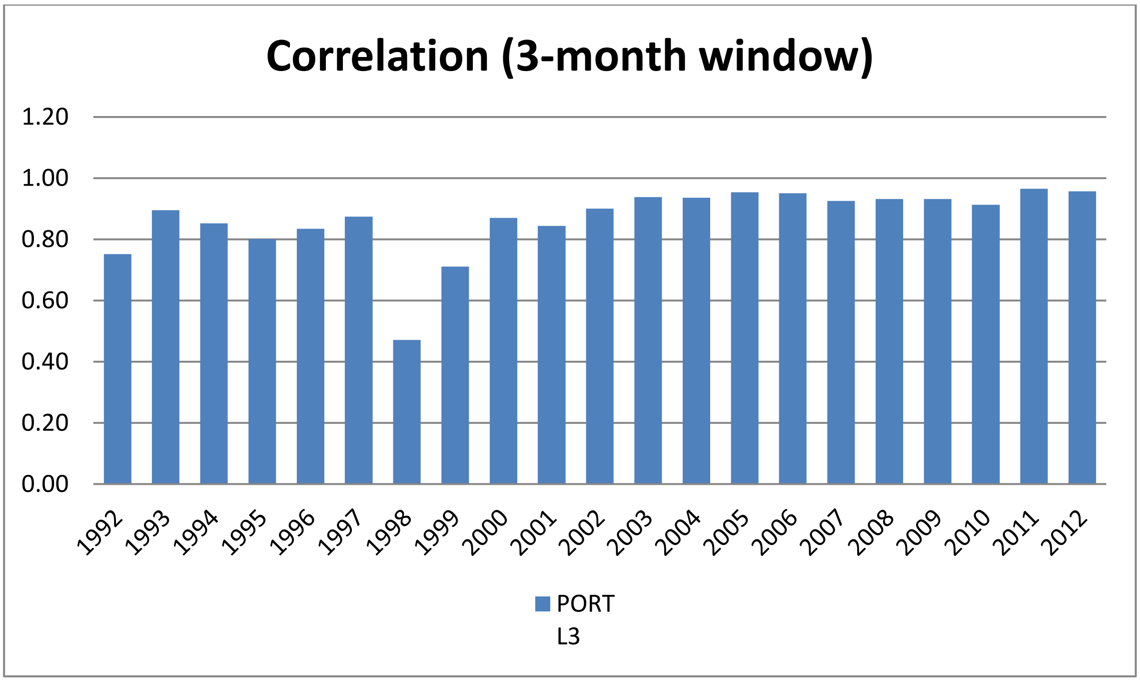

Figure 5.5-24 Correlation (3-month window)

In Figure 5.5-26, we display the correlation chart for our 3-month annualized window. It presents the correlations between our portfolios and the S&P 1500. The correlation overall is quite high with, for example, in 2012 the portfolio exhibiting a positive correlation of 0.96 with the S&P 1500. The correlation is indicating that the portfolio moves in line with the S&P 1500, offering little diversification for investors willing to use our portfolio in a fund. (Refer to Appendix E.)

5.5.6 Volatility

We show in this part graphics representing the return on our long portfolio against the market and the volatility for both. This helps us to understand to what extent our strategy is more volatile by comparing returns for the risk taken. The results show that for not a much higher volatility our strategy is able to generate higher return than the market.

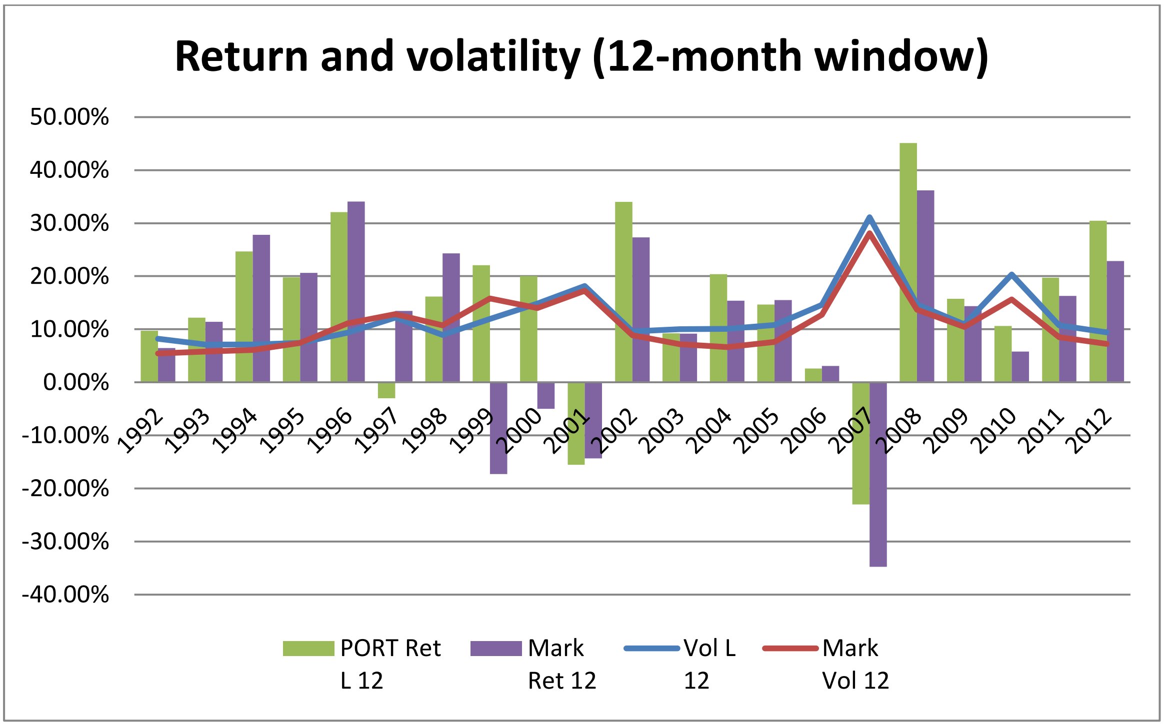

Figure 5.5-25 Return and volatility for long portfolio against market (12-month window)

In Figure 5.5-27, we present annualized returns and annualized volatility on a 12-month window horizon. The results are showing that for not a much greater volatility we are able to generate higher return. For illustration purposes, during periods of high market volatility investors are likely to see return to be negative, for instance in 2007, in 2001 or in 1997.

In the following figure, 5.5-28, we represent a scatter diagram with, in the y-axis, the return of our long portfolio against the market and on the x-axis the volatility of our long portfolio against the volatility of the market on a 12-month annualized window. (Refer to Appendix F.)

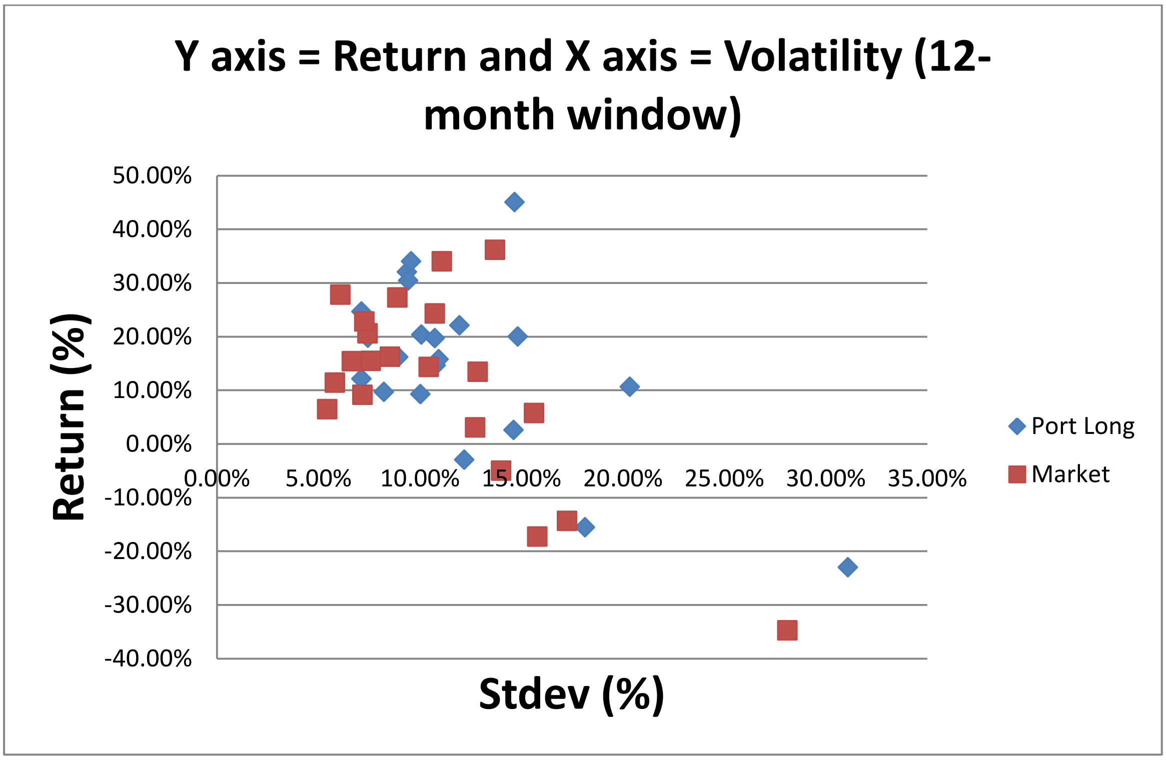

Figure 5.5-26 Scatter diagram return and volatility (12-month window)

Figure 5.5-28 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot investors will be able to understand that for the same level of risk our strategy is delivering higher return, as suggested by the concentration on around 10% standard deviation. (Refer to Appendix F.)

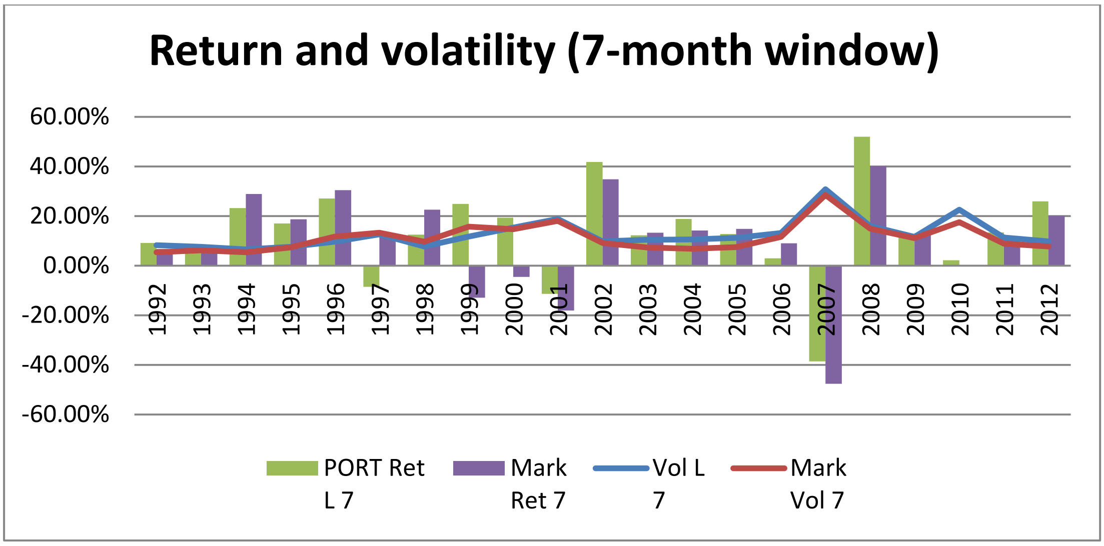

Figure 5.5-29 Return and volatility for long portfolio against market (7-month window)

In Figure 5.5-29, we present annualized returns and annualized volatility on a 7-month window horizon. The results are showing that for not a much greater volatility we are able to generate higher return. For illustration purposes, during periods of high market volatility investors are likely to see return to be negative, for instance in 2007, in 2001 or in 1997.

As an example, in 2007 the portfolio has a negative return of -38.65% for a volatility of 30.78% whilst the market has a negative return of -47.68% for a volatility of 28.48%, meaning that our strategy relative to the market is not very risky even during crisis times.

In the following figure, 5.5-30, we represent a scatter diagram with, in the y-axis, the return of our long-short portfolio against the market and on the x-axis the volatility of our long-short portfolio against the volatility of the market on a 7-month annualized window. (Refer to Appendix F.)

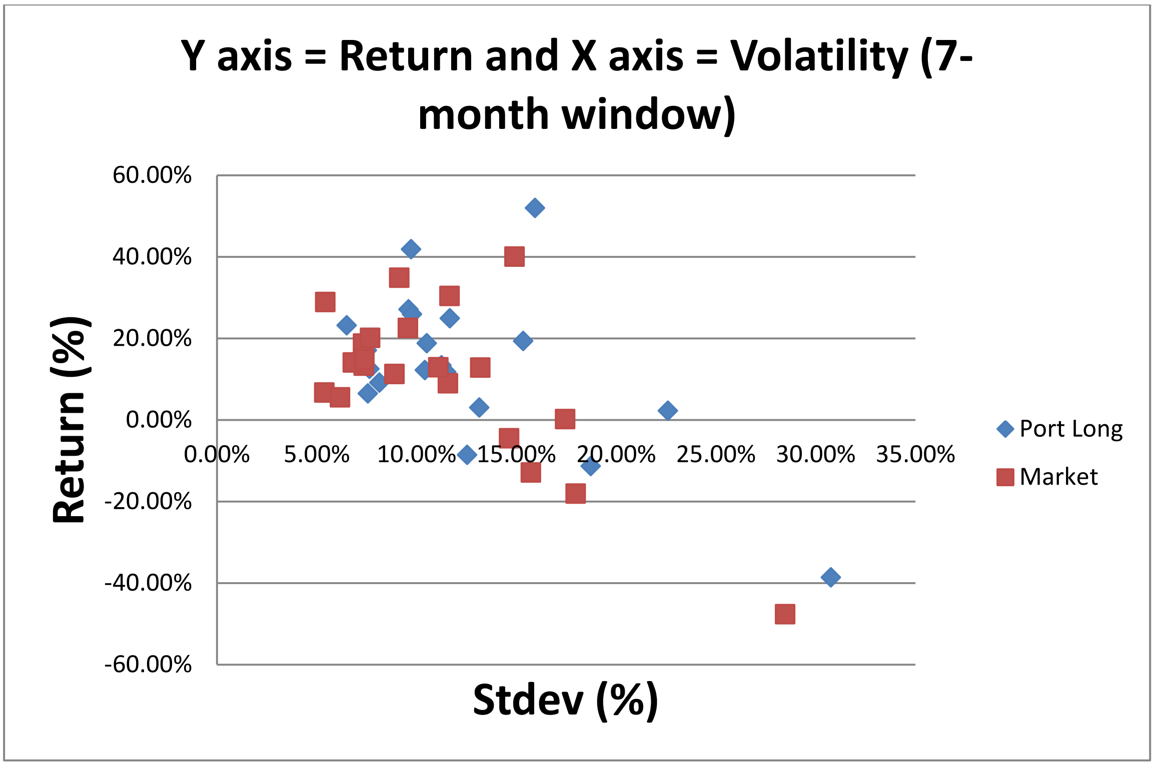

Figure 5.5-27 Scatter diagram return and volatility (7-month window)

The chart in Figure 5.5-30 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot, investors will be able to understand that for the same level of risk our strategy is delivering higher return, as suggested by the concentration on around 10% standard deviation. (Refer to Appendix F.)

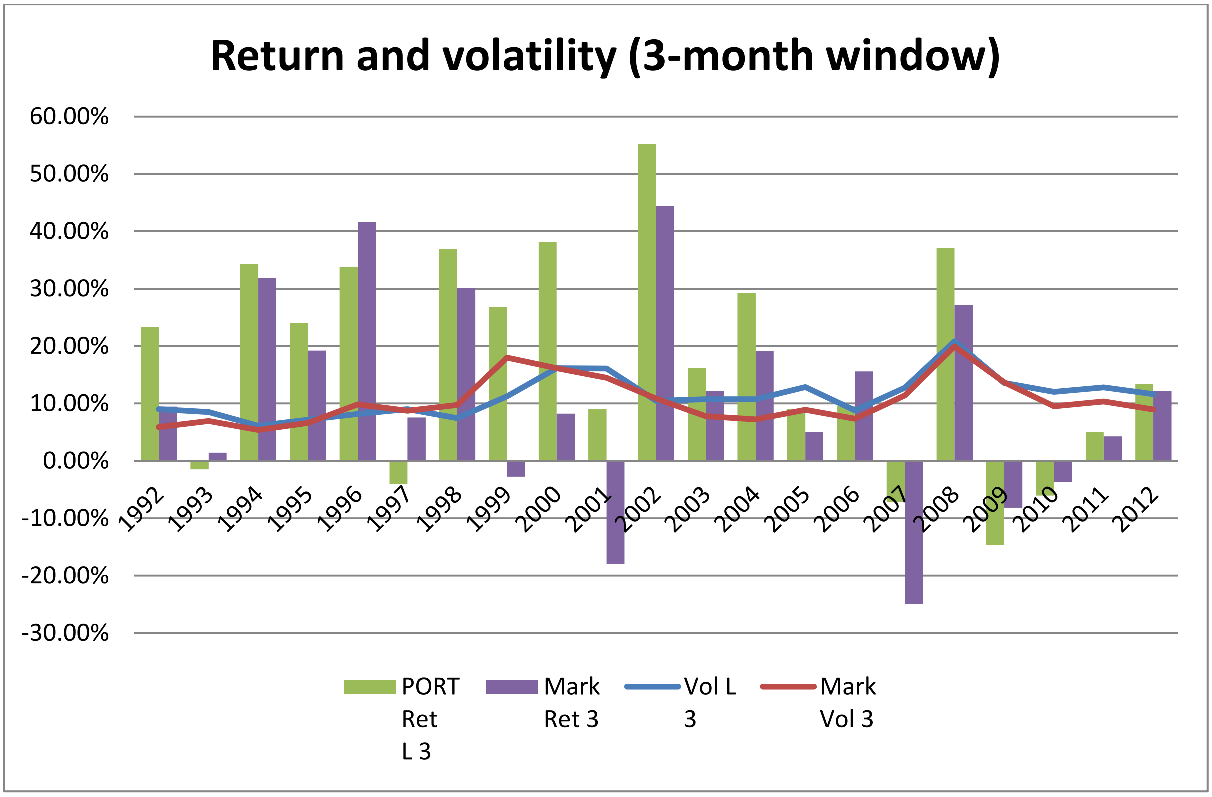

Figure 5.5-28 Return and volatility for long portfolio against market (3-month window)

In Figure 5.5-31, we present annualized returns and annualized volatility on a 3-month window horizon. The results are showing that for not a much greater volatility we are able to generate higher return. For illustration purposes, during periods of high market volatility investors are likely to see return to be negative, for instance in 2007, in 2001 or in 1997.

As an example, in 2007 the portfolio has a negative return of -7.14% for a volatility of 12.76% whilst the market has a negative return of -24.97% for a volatility 11.43%, meaning that our strategy relative to the market is not very risky even during crisis times.

In the following figure, 5.5-32, we represent a scatter diagram with, in the y-axis, the return of our long-short portfolio against the market and on the x-axis the volatility of our long-short portfolio against the volatility of the market on a 3-month annualized window. (Refer to Appendix F.)

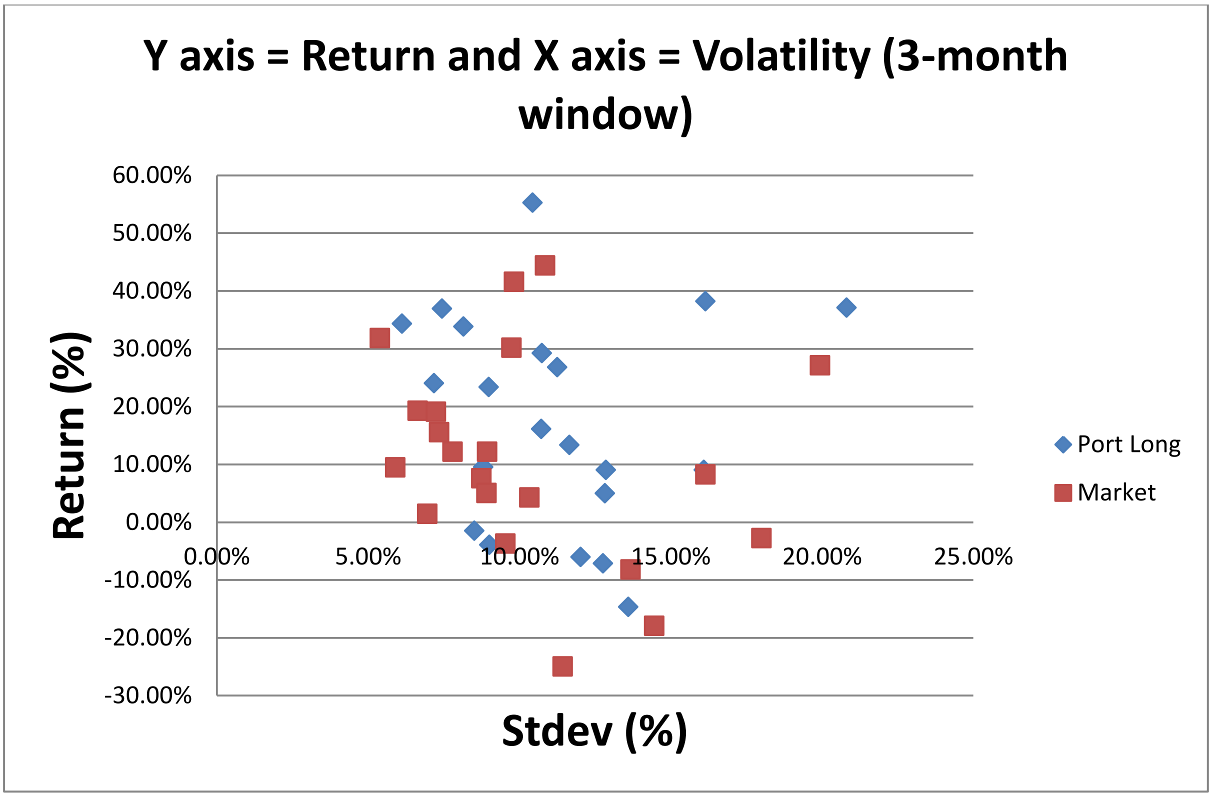

Figure 5.5-29 Scatter diagram return and volatility (3-month window)

Figure 5.5-32 displays the risk return scatterplot to illustrate the risk versus the return of our long-short portfolio. The return is on the y-axis while the risk is on the x-axis. Here the risk is defined as the standard deviation (volatility). The scatterplot shows as well the risk return of the benchmark for illustration purposes. From the scatterplot, investors will be able to understand that for the same level of risk our strategy is delivering higher return, as suggested by the concentration on around 10% standard deviation. (Refer to Appendix F.)

5.6 Conclusion

This chapter has examined the impact of return on equity as a momentum strategy. Consistent with the literature, this chapter finds that the momentum return on equity trading strategy is profitable as examined. The literature highlights the connection between return on equity and momentum strategies and this chapter extends the literature by examining the impact of return on equity as a momentum strategy in the US market.

Therefore, the main goal of this chapter was to develop a momentum strategy using return on equity (ROE) as a variable. Using daily data from 1992 to 2012, we examined whether our long portfolio is able to deliver subsequent return to investors. This portfolio was then back tested using different risk metrics used in the industry over the period 1992 to 2012; in order to do so we applied some risk-adjusted return measures. Our strategy has not been tested using transaction costs; however, we believe that, due to the high performance, this will not affect the strategy while producing positive returns. Finally, we highly believe the strategy can be used in the current environment and can help investors to increase their wealth.

5.7 Appendices

5.7.1 Appendix A

In Table 5.7-1 below we present the different returns expressed as a percentage earned by our long portfolio for the three frequencies' periods. As well, we display return for the benchmark S&P 1500.

Table 5.7-1 Displays return for the different time horizons on the long portfolio, the market and the excess return

	PORT L 12	PORT L 7	PORT L 3	Mark 12	Mark 7	Mark 3	Excess Return 12	Excess Return 7	Excess Return 3
1992	9.69%	9.09%	23.34%	6.45%	6.70%	9.46%	3.25%	2.40%	13.88%
1993	12.16%	6.46%	-1.47%	11.41%	5.47%	1.44%	0.76%	0.99%	-2.91%
1994	24.68%	23.15%	34.30%	27.82%	28.86%	31.84%	-3.14%	-5.71%	2.46%
1995	19.76%	17.04%	24.01%	20.63%	18.67%	19.24%	-0.88%	-1.63%	4.76%
1996	32.09%	27.04%	33.81%	34.04%	30.36%	41.57%	-1.95%	-3.32%	-7.77%
1997	-2.98%	-8.62%	-3.96%	13.45%	12.80%	7.57%	-16.43%	-21.42%	-11.52%
1998	16.19%	12.45%	36.92%	24.29%	22.50%	30.15%	-8.10%	-10.05%	6.77%
1999	22.09%	24.86%	26.82%	-17.27%	-12.96%	-2.76%	39.36%	37.82%	29.58%
2000	20.04%	19.29%	38.20%	-4.98%	-4.55%	8.23%	25.01%	23.83%	29.97%
2001	-15.55%	-11.38%	9.03%	-14.33%	-18.11%	-17.95%	-1.22%	6.72%	26.97%
2002	34.03%	41.80%	55.23%	27.31%	34.82%	44.40%	6.72%	6.97%	10.83%
2003	9.26%	12.16%	16.13%	9.18%	13.23%	12.19%	0.08%	-1.08%	3.95%
2004	20.37%	18.75%	29.26%	15.41%	14.09%	19.12%	4.96%	4.66%	10.13%
2005	14.64%	12.67%	9.04%	15.48%	14.82%	5.01%	-0.84%	-2.15%	4.03%
2006	2.61%	2.97%	9.54%	3.07%	8.99%	15.56%	-0.47%	-6.03%	-6.03%
2007	-23.00%	-38.65%	-7.14%	-34.76%	-47.68%	-24.97%	11.76%	9.03%	17.83%
2008	45.08%	51.97%	37.12%	36.19%	40.04%	27.13%	8.89%	11.92%	9.99%
2009	15.77%	11.71%	-14.70%	14.37%	12.84%	-8.17%	1.40%	-1.13%	-6.53%
2010	10.64%	2.18%	-6.06%	5.77%	0.17%	-3.71%	4.87%	2.01%	-2.34%
2011	19.74%	13.37%	4.98%	16.27%	11.22%	4.26%	3.47%	2.16%	0.72%
2012	30.46%	25.93%	13.37%	22.84%	20.13%	12.17%	7.62%	5.80%	1.20%

5.7.2 Appendix B

In Table 5.7-2 below we present the different maximum drawdown known by our portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 5.7-2 Displays the maximum drawdown numbers for the different time horizons on the long portfolio and the market

Maximum drawdown	PORT L12	PORT L7	PORT L3	MARK 12	MARK 7	MARK 3
1992	-4.8%	-4.0%	-3.1%	-3.3%	-3.3%	-2.9%
1993	-5.1%	-5.1%	-5.1%	-3.7%	-3.7%	-3.7%
1994	-4.5%	-4.5%	-1.5%	-2.5%	-2.3%	-1.3%
1995	-5.6%	-5.6%	-3.4%	-6.1%	-6.1%	-3.1%
1996	-7.3%	-7.3%	-2.0%	-8.9%	-8.9%	-2.5%
1997	-22.3%	-22.3%	-5.6%	-13.3%	-13.3%	-4.5%
1998	-8.5%	-8.5%	-2.8%	-4.8%	-4.6%	-2.7%
1999	-6.6%	-6.3%	-4.5%	-30.0%	-18.8%	-10.4%
2000	-20.2%	-20.2%	-6.5%	-29.7%	-29.7%	-7.4%
2001	-32.4%	-21.0%	-8.8%	-26.1%	-25.2%	-10.4%
2002	-5.3%	-3.4%	-2.3%	-5.0%	-3.2%	-2.5%
2003	-9.0%	-9.0%	-5.1%	-4.2%	-3.9%	-3.4%
2004	-6.5%	-6.5%	-5.8%	-3.8%	-3.8%	-3.4%
2005	-9.0%	-9.0%	-9.0%	-5.0%	-5.0%	-5.0%
2006	-14.9%	-11.8%	-4.8%	-13.9%	-7.6%	-3.2%
2007	-62.5%	-62.5%	-8.3%	-68.7%	-64.8%	-12.1%
2008	-6.3%	-6.3%	-6.3%	-6.5%	-6.5%	-6.5%
2009	-10.6%	-10.6%	-8.9%	-7.9%	-7.9%	-7.9%
2010	-20.2%	-20.2%	-6.6%	-16.1%	-16.1%	-5.9%
2011	-5.1%	-5.1%	-4.9%	-4.6%	-13.2%	-4.4%
2012	-3.9%	-3.9%	-3.9%	-3.7%	-3.7%	-3.7%

5.7.3 Appendix C

In Table 5.7-3 below we present the different beta generated by our portfolios for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 5.7-3 Displays the beta numbers for the different time horizons on the long portfolio

Beta	PORT L12	PORT L7	PORT L3
1992	1.11	1.09	1.14
1993	1.09	1.10	1.09
1994	0.97	1.00	0.97
1995	0.85	0.86	0.87
1996	0.74	0.73	0.69
1997	0.83	0.85	0.90
1998	0.51	0.46	0.36
1999	0.55	0.53	0.44
2000	0.93	0.92	0.87
2001	0.94	0.94	0.94
2002	0.95	0.94	0.87
2003	1.30	1.32	1.29
2004	1.39	1.43	1.39
2005	1.33	1.42	1.38
2006	1.07	1.06	1.14
2007	1.07	1.05	1.03
2008	0.99	0.99	0.97
2009	0.94	0.94	0.93
2010	1.25	1.26	1.15
2011	1.19	1.20	1.20
2012	1.20	1.19	1.25

5.7.4 Appendix D

In Table 5.7-4 below we present the different ratios used to measure risks and the volatility known by our portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 5.7-4 Displays the different ratios used to measure risks and the volatility across the different time horizons on the long portfolio

	L 12 Sharpe ratio	L 7 Sharpe ratio	L 3 Sharpe ratio	L 12 IR	L 7 IR	L 3 IR	L 12 Sortino ratio	L 7 Sortino ratio	L 3 Sortino ratio	L 12 Treynor ratio	L 7 Treynor ratio	L 3 Treynor ratio	Jensen's 12	Jensen's 7	Jensen's 3
1992	1.172	1.109	2.589	1.175	1.111	2.566	1.711	1.610	3.298	0.042	0.038	0.160	2.53	1.79	12.38
1993	1.699	0.847	-0.179	1.701	0.851	-0.171	2.570	1.275	-0.265	0.066	0.013	-0.059	-0.25	0.47	-3.01
1994	3.452	3.546	5.595	3.450	3.540	5.541	5.149	5.668	10.986	0.203	0.182	0.303	-2.23	-5.55	3.44
1995	2.645	2.258	3.337	2.644	2.257	3.307	3.857	3.100	6.544	0.174	0.139	0.219	2.26	0.88	7.24
1996	3.417	2.810	4.139	3.413	2.805	4.100	4.155	3.237	6.097	0.365	0.303	0.416	6.79	4.93	4.92
1997	-0.248	-0.691	-0.444	-0.243	-0.684	-0.434	-0.373	-0.993	-0.736	-0.096	-0.159	-0.099	-14.11	-19.48	-10.66
1998	1.803	1.619	4.954	1.804	1.620	4.906	3.216	2.932	9.135	0.220	0.162	0.887	3.78	2.06	25.74
1999	1.842	2.126	2.380	1.841	2.122	2.358	3.191	4.242	4.113	0.310	0.375	0.491	31.5	31.57	27.71
2000	1.348	1.253	2.361	1.348	1.252	2.338	2.097	1.881	3.881	0.163	0.156	0.381	24.56	23.36	30.68
2001	-0.860	-0.610	0.558	-0.854	-0.605	0.555	-1.483	-1.064	1.042	-0.219	-0.175	0.043	-2.11	5.56	25.60
2002	3.547	4.287	5.286	3.542	4.276	5.233	5.573	6.638	7.570	0.306	0.392	0.580	8.07	9.06	16.58
2003	0.918	1.162	1.499	0.920	1.162	1.487	1.427	1.740	2.234	0.033	0.054	0.086	-2.63	-5.24	0.40
2004	2.015	1.777	2.718	2.014	1.775	2.693	3.283	2.937	4.579	0.110	0.096	0.175	-1.113	-19.84	2.69
2005	1.352	1.133	0.699	1.352	1.134	0.695	1.979	1.765	1.094	0.072	0.054	0.029	-5.99	-8.37	2.13
2006	0.175	0.222	1.076	0.178	0.225	1.070	0.260	0.312	1.610	-0.022	-0.019	0.040	-0.68	-6.51	-8.10
2007	-0.741	-1.257	-0.564	-0.738	-1.251	-0.554	-1.036	-1.683	-0.879	-0.262	-0.417	-0.118	14.1	11.17	18.44
2008	3.068	3.257	1.781	3.063	3.248	1.764	4.521	4.900	2.894	0.404	0.475	0.330	9.10	12.31	10.62
2009	1.438	1.013	-1.084	1.438	1.014	-1.068	2.179	1.585	-1.635	0.115	0.071	-0.213	2.30	-0.33	-7.04
2010	0.520	0.094	-0.508	0.521	0.096	-0.498	0.706	0.134	-0.809	0.045	-0.022	-0.096	3.39	1.95	-1.76
2011	1.832	1.184	0.385	1.832	1.184	0.384	2.906	1.974	0.617	0.124	0.070	0.000	0.35	-0.04	-0.11
2012	3.225	2.646	1.143	3.221	2.641	1.134	4.437	3.635	1.439	0.212	0.176	0.067	3.09	1.93	-1.79
Max	3.547	4.287	5.595	3.542	4.276	5.541	5.573	6.638	10.986	0.404	0.475	0.887	31.50	31.57	30.68
Min	-0.860	-1.257	-1.084	-0.854	-1.251	-1.068	-1.483	-1.683	-1.635	-0.262	-0.417	-0.213	-14.11	-19.84	-19.84
Mean	1.601	1.418	1.796	1.601	1.418	1.781	2.396	2.182	2.991	0.113	0.094	0.173	2.30	1.79	3.44
Median	1.699	1.184	1.499	1.701	1.184	1.487	2.570	1.881	2.234	0.115	0.071	0.086	3.93	1.98	7.43

5.7.5 Appendix E

In Table 5.7-5 below we present the correlation measured across by our portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 5.7-5 Displays the correlation measured across the different time horizons on the portfolio

Correl	PORT L12	PORT L7	PORT L3
1992	0.73	0.72	0.75
1993	0.89	0.89	0.90
1994	0.82	0.83	0.85
1995	0.84	0.84	0.80
1996	0.88	0.88	0.83
1997	0.88	0.90	0.87
1998	0.61	0.58	0.47
1999	0.73	0.71	0.71
2000	0.87	0.87	0.87
2001	0.89	0.90	0.84
2002	0.88	0.88	0.90
2003	0.93	0.93	0.94
2004	0.92	0.93	0.94
2005	0.94	0.94	0.95
2006	0.93	0.93	0.95
2007	0.97	0.97	0.93
2008	0.93	0.93	0.93
2009	0.89	0.91	0.93
2010	0.96	0.97	0.91
2011	0.95	0.95	0.97
2012	0.92	0.94	0.96

5.7.6 Appendix F

In Table 5.7-6 below we present the returns and volatility measured across by our long-short portfolio for the three frequencies' periods. This represents a summary of the figures discussed above.

Table 5.7-6 Displays the returns and volatility measured across the different time horizons on the long-short portfolio against the market

	Vol L 12	Vol L 7	Vol L 3	PORT Ret L 12	PORT Ret L 7	PORT Ret L 3	Mark Vol 12	Mark Vol 7	Mark Vol 3	Mark Ret 12	Mark Ret 7	Mark Ret 3
1992	8.23%	8.16%	8.99%	9.69%	9.09%	23.34%	5.44%	5.39%	5.90%	6.45%	6.70%	9.46%
1993	7.13%	7.57%	8.51%	12.16%	6.46%	-1.47%	5.82%	6.18%	6.96%	11.41%	5.47%	1.44%
1994	7.13%	6.51%	6.12%	24.68%	23.15%	34.30%	6.08%	5.43%	5.39%	27.82%	28.86%	31.84%
1995	7.45%	7.52%	7.18%	19.76%	17.04%	24.01%	7.43%	7.32%	6.64%	20.63%	18.67%	19.24%
1996	9.38%	9.61%	8.16%	32.09%	27.04%	33.81%	11.09%	11.66%	9.82%	34.04%	30.36%	41.57%
1997	12.20%	12.55%	9.02%	-2.98%	-8.62%	-3.96%	12.86%	13.20%	8.75%	13.45%	12.80%	7.57%
1998	8.95%	7.66%	7.44%	16.19%	12.45%	36.92%	10.74%	9.57%	9.74%	24.29%	22.50%	30.15%
1999	11.96%	11.67%	11.25%	22.09%	24.86%	26.82%	15.80%	15.73%	18.00%	-17.27%	-12.96%	-2.76%
2000	14.83%	15.35%	16.15%	20.04%	19.29%	38.20%	14.01%	14.65%	16.15%	-4.98%	-4.55%	8.23%
2001	18.15%	18.74%	16.09%	-15.55%	-11.38%	9.03%	17.26%	17.98%	14.45%	-14.33%	-18.11%	-17.95%
2002	9.58%	9.74%	10.44%	34.03%	41.80%	55.23%	8.90%	9.15%	10.85%	27.31%	34.82%	44.40%
2003	10.03%	10.42%	10.73%	9.26%	12.16%	16.13%	7.18%	7.36%	7.79%	9.18%	13.23%	12.19%
2004	10.08%	10.53%	10.75%	20.37%	18.75%	29.26%	6.65%	6.81%	7.24%	15.41%	14.09%	19.12%
2005	10.80%	11.14%	12.86%	14.64%	12.67%	9.04%	7.59%	7.39%	8.91%	15.48%	14.82%	5.01%
2006	14.62%	13.16%	8.81%	2.61%	2.97%	9.54%	12.73%	11.58%	7.35%	3.07%	8.99%	15.56%
2007	31.10%	30.78%	12.76%	-23.00%	-38.65%	-7.14%	28.11%	28.48%	11.43%	-34.76%	-47.68%	-24.97%
2008	14.68%	15.94%	20.81%	45.08%	51.97%	37.12%	13.72%	14.92%	19.94%	36.19%	40.04%	27.13%
2009	10.93%	11.51%	13.60%	15.77%	11.71%	-14.70%	10.44%	11.10%	13.68%	14.37%	12.84%	-8.17%
2010	20.35%	22.60%	12.02%	10.64%	2.18%	-6.06%	15.63%	17.46%	9.54%	5.77%	0.17%	-3.71%
2011	10.75%	11.25%	12.83%	19.74%	13.37%	4.98%	8.54%	8.91%	10.34%	16.27%	11.22%	4.26%
2012	9.43%	9.78%	11.66%	30.46%	25.93%	13.37%	7.27%	7.68%	8.94%	22.84%	20.13%	12.17%

5.7.7 Appendix G

Table 5.7-7 Displays the number of stocks every year for the momentum strategy

	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
1992	108	46	20	11	6	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1993		236	139	61	24	15	7	2	2	1	1	0	0	0	0	0	0	0	0	0	0
1994			278	129	49	23	8	3	3	1	1	0	0	0	0	0	0	0	0	0	0
1995				266	110	53	21	10	3	2	1	0	0	0	0	0	0	0	0	0	0
1996					262	122	50	21	10	3	2	1	0	0	0	0	0	0	0	0	0
1997						330	124	53	25	9	5	3	2	1	0	0	0	0	0	0	0
1998							258	117	41	13	7	4	3	2	0	0	0	0	0	0	0
1999								258	90	23	9	4	3	2	0	0	0	0	0	0	0
2000									289	70	31	15	9	5	1	1	0	0	0	0	0
2001										156	67	27	16	7	2	1	0	0	0	0	0
2002											197	72	43	19	8	2	0	0	0	0	0
2003												311	166	87	37	17	3	0	0	0	0
2004													430	226	108	48	9	0	0	0	0
2005														470	227	101	32	3	1	1	1
2006															409	185	62	10	4	4	4
2007																355	118	22	10	7	5
2008																	253	40	18	12	8
2009																		119	57	34	18
2010																			302	148	65
2011																				511	193
2012																					308

Table 5.7-8 Displays the percentage of stocks every year for the momentum strategy

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
1992	43%	19%	10%	6%	2%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1993		59%	26%	10%	6%	3%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1994			46%	18%	8%	3%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1995				41%	20%	8%	4%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1996					47%	19%	8%	4%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
1997						38%	16%	8%	3%	2%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%
1998							45%	16%	5%	3%	2%	1%	1%	0%	0%	0%	0%	0%	0%	0%
1999								35%	9%	3%	2%	1%	1%	0%	0%	0%	0%	0%	0%	0%
2000									24%	11%	5%	3%	2%	0%	0%	0%	0%	0%	0%	0%
2001										43%	17%	10%	4%	1%	1%	0%	0%	0%	0%	0%
2002											37%	22%	10%	4%	1%	0%	0%	0%	0%	0%
2003												53%	28%	12%	5%	1%	0%	0%	0%	0%
2004													53%	25%	11%	2%	0%	0%	0%	0%
2005														48%	21%	7%	1%	0%	0%	0%
2006															45%	15%	2%	1%	1%	1%
2007																33%	6%	3%	2%	1%
2008																	16%	7%	5%	3%
2009																		48%	29%	15%
2010																			49%	22%
2011																				38%

CONCLUDING REMARKS AND FURTHER WORK

The rational of this thesis was to develop a value investing strategy to be able to distinguish winners from losers and if efficient as stated by Piotroski(2000) this should shift the distribution earn by an investors.

Using data from Compustat and CRSP from 1991 to 2012, we examined the use of the F-Score on the S&P 1500 screening for stocks in order to form some investment strategies. The different portfolios were then backtested using both statistical and risk-adjusted measures but also in terms of performances. In order to do so we applied a realistic way of forming a long and a short portfolio and assessed the performances on different windows horizons.

Not allowing for transactions costs is not affecting our trading strategies due to the high performances as we retained positive returns. Our long-short portfolio appears to be the most interesting and fit within the contextual environment.

Portfolio combination i.e. value and momentum, despite interesting performances failed to produce higher return than our initial strategies i.e. our so called market neutral portfolio.

Further work is also needed to compare the results with a simple strategies such as price to earnings for example and also adding more criteria's when using the f-score to perhaps get a better screening such as for example distance to default or dividend yield.

Also some improvement can be made by making the process more robust or faster by using programming languages as C++ or java in order to make the investment for the investor as quickly as possible.

Finally adding transaction costs could be part of a refinement in order to have a more realistic trading strategy and can account for all the assumptions.

However, despite the limitations of this thesis, we clearly developed a reasonably accurate investment tool that can help investors to identify winners from losers in a universe of stocks and subsequently simulated a profitable portfolio that outperformed the market.

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